ESSAYS ON APPLIED MICROECONOMICS IN HEALTH AND LABOR

A DISSERTATION SUBMITTED TO THE GRADUATE DIVISION OF THE UNIVERSITY OF HAWAIʻI AT MĀNOA IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

IN

ECONOMICS

May 2023

By
Maya L. Ward

Dissertation Committee:

Timothy Halliday, Chairperson
Teresa Molina
Peter Fuleky
Justin Tyndall
Neil Frazer

Keywords: networks, health, labor, personality, household bargaining, domestic violence

Acknnowledgements

I would like to thank my dissertation committee members for their time in guiding me throughout this last phase of my academic journey, and helping me become a researcher. I sincerely appreciate all comments and feedback received during presentations and revisions of drafts over the years. I would like to especially thank my committee chair, Tim Halliday, for his constant support and mentorship since my first year as a PhD student. I am grateful for your ability to push me beyond what I thought was possible. Thank you to all of my peers with whom I crossed paths during my time in the program; each of you helped me in some way to get to this point. Special thanks to Rachel Inafuku for her friendship and collaboration on work presented in this dissertation.

I would also like to thank the family and friends I left behind on the mainland, who continued to support me from afar. Your calls and cards meant more than you know.

Last, thank you to my husband Steven for his unwavering support from the application process to the final defense. Thank you for taking a leap of faith and moving over 5,000 miles and an ocean away so we could live in this paradise, and so I could pursue my dream.

Abstract

This dissertation applies econometric techniques to topics in health and labor economics in Colombia, the United States, and India. The first chapter examines the relationship between domestic violence legislation in Colombia and intra-household bargaining power for women. I use the Demographic Health Survey (DHS) Waves V to VII with a difference-in-difference strategy to causally identify the relationship between the implementation of a gender policy from the law and an increase in the household bargaining power of women. I find evidence of an overall positive relationship, indicating potential spillover effects. As intra-household bargaining power is traditionally hard to influence, this could signal an indirect strategy to influence this and other modes of female empowerment.

The second chapter is in collaboration with Rachel Inafuku on the effects of economic downturns on labor market outcomes across the Big Five personality traits. There is still a large amount of unexplained variation in various labor market outcomes after accounting for observable characteristics (age, gender, education, etc) indicating that unobservable characteristics (personality, work ethic, etc) may also play an important role. While the psychology literature has investigated the relationship between personality and labor market outcomes, there are far fewer studies that incorporate personality traits within economics. Furthermore, there is not a clear consensus within the economics literature that determines how the labor market outcomes of workers varies across personality traits. Using the 1997 cohort of the National Longitudinal Survey of Youth (NLSY), this study looks at how economic downturns impact labor market outcomes differentially across the "Big Five" personality traits. We find that those who report higher levels of emotional instability tend to see more

unemployment insurance take up and fewer weeks of employment during economic downturns relative to those who are more emotionally stable. Additionally, the effects do not seem to be driven by employer discrimination, as it may be that workers with higher levels of emotional instability are less productive during recessions.

The final chapter assesses the impact of ethnic networks on healthcare use in India. Simply increasing availability of healthcare services alone does not increase usage, but investigation into ethnic networks may provide insight into the mechanisms of decision making regarding the services. Using cross-sectional data from Wave 4 (2015-2016) of the National Family Health Survey (NFHS), I explore how networks affect usage for maternal health services, repeating regressions for language-district, language-social, and district-social groups. I find evidence of network influence for all delivery and prenatal care outcomes for the language-district network definition, evidence for institutional delivery and prenatal care as well as a first trimester prenatal checkup for district-social groups, and little evidence for network effects for the language-social groups network definition. This suggests that ethnic networks are used for some maternal healthcare decisions, but that the definition and construction of that network for the analysis matters. District appears to be an important factor in networks that affect healthcare use, while social groups (as defined by the data) seems to not capture networks as well.

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Chapter 1

Intra-household Bargaining and Domestic Violence in Colombia: Effects of Law 1257

Maya Ward

1.1 Introduction

There is a broad academic literature looking at how increases in bargaining power for women affects intimate partner violence (IPV). Improved female economic power can reduce the incidence of IPV in the longterm (Raj et al. [2018]) and short-term (Eggers del Campo and Steinert [2022]), with cash vouchers (Hidrobo et al. [2016], Bobonis et al. [2013], Bobonis et al. [2015]) or microfinance programs(Murshid et al. [2016], Murshid [2016]). However, some studies show this can have a backlash effect and increase IPV in certain cases (Murshid [2016], Ericsson [2020]), making the outcome of policies uncertain. Increasing economic empowerment via employment in developing countries has also been shown to reduce IPV, as in Molina and Tanaka [2021] and Bhattacharyya et al. [2011], and decision-making or bargaining power (Pankaj and Tankha [2010]). Bargaining power refers to a person's (or party's) ability to negotiate, ideally from equal starting points and resources. However, when one party has an advantage, the starting statuses are unequal; this level of (in)equality is determined by the "threat points" or fallback options of each person (Agarwal [1997]). It generally focuses on four main aspects: economic, social networks, political/institutional, and social or cultural norms (Agarwal [1997]), the latter two of which are often neglected when modeling (Doss [2012]). Changes in one or more of these aspects of bargaining power has been linked to outcomes such as child health and education, decision-making, and violence (Doss [2012]). Since this law purportedly gives victims of violence support outside of their household and network, the institutional changes from Law 1257 could have an impact on household decisions. Using micro data from Ghana, Nuhu, Ahmed Salim [2015] finds that child health decisions are impacted by women's bargaining power in the household, and are mediated through domestic violence laws. Following this, I hope to discover if women's bargaining power, as indexed through decision-making authority outcomes, are impacted in Colombia as well.

In an effort to decrease violence against women, a number of policies were created across Latin America, including Law 1257 in Colombia. However, liberating women from intimate partner violence is just one dimension of their welfare in the household. The question is, if this dimension is addressed, will it spill over into others as well? In this paper, I examine Law 1257 (Colombia Government [2008]) passed in 2008 in Colombia, and the extent to which this policy designed to affect IPV may have effects that spill over into the household bargaining power of women. From Durevall [2021], I know that this law causally decreased incidences of physical and sexual violence by an average of 4 and 1.2 percentage points, respectively. Therefore, my paper will also investigate not just if the policy created spillover effects, but if confirmed success at reducing IPV translates to any success at increasing household bargaining power.

This additionally contributes to the larger literature on female empowerment, which looks at improving the lives of women by closing the gender gap in education, employment, and political seats in national parliaments (Essayag [2013], Kabeer [2005]). Studies such as Duflo [2003] and Lépine and Strobl [2013] show how increasing one or more of these aspects not only improves the lives of the women themselves, but often that of those around them as well. These improvements range from health and healthcare (Mainuddin et al. [2015], Ahmed et al. [2010], Novignon et al. [2019]), to education (Hatlebakk and Gurung [2016]) and even economic development via human capital (Doepke and Tertilt [2019], Duflo [2012]). Since the implementation of Law 1257 includes a gender policy encompassing some or all of these aspects, the Law can be seen (once implemented) as increasing female empowerment, placing women on more equal status with men.

I propose that the decrease in incidences of IPV could affect the day-to-day decision-making power of women through one of two ways. First, by decreasing physical IPV, I could assume that women are less threatened by their partners in their day-to-day lives, thereby decreasing stress and allowing them to focus on other tasks [1]. The ongoing instance of IPV (which includes threats and actual physical violence) is shown to be stressful by creating and perpetuating PTSD in victims (Woods et al. [2008], Fragkaki et al. [2016]). This would mean that reducing IPV could reduce the effects of this stress, improving the lives of the women and empowering them. If they feel less threatened and potentially more confident in their position, they could be more likely to assert themselves and their opinions, leading to increased decision-making. Secondly, IPV was decreased by the creation of institutional change and creating more of a social safety net for victims. This means that the victims have more options for support outside of their household, increasing their options for independence if they choose to leave, i.e., increasing their bargaining power. If women are more secure in their outside options, they may be less afraid of asserting themselves, knowing they have another opportunity available. This then increases their bargaining power in daily life within the household.

I find evidence of a relationship between the adoption of a gender policy from Law 1257 and intra-household bargaining, with three significant coefficients from the items in the bargaining index, and the index itself. One other coefficient is positive but not significant, while the remaining two are negative, with one significant and one not significant. These effects are seen despite data limitations, indicating potentially underestimated results. The findings suggest that policies that are targeted to impact one aspect of bargaining power may have spillover effects to other elements of it, and that the original effects of the policy on bargaining power could be underestimated if it is not taken into account. The paper continues as follows: Section 2 provides institutional background on Colombia and Law 1257, Section 3 discusses the data and empirical methodology, Section 4 presents the results and robustness checks, and Section 5 concludes.

[1] This is the inverse of the finding that IPV causes stress biologically (Yim and Kofman [2019])

1.2 Institutional Background

1.2.1 Structure of Government

Colombia is comprised of 32 departments plus the capital district of Bogotá, whose governors each report to the central government and the president. At the local level, the city mayors report to the governors. Each level's leader controls the funds for their area, and oversees the implementation of any policies. The governors can work together to implement various initiatives if necessary, and share funds accordingly. The system is highly centralized with three branches of government: the executive, judicial, and representative (congress). The justice department hears the cases regarding infractions against the national laws.

To implement policies mandated from the national government, it is up to each department to organize and oversee the direct implementation. The local governments are sometimes given funds to do so by the national government, and they can also pool resources amongst themselves as well.

1.2.2 History of Legislation

Over the past fifteen years, there has been a concerted effort to promote the welfare of women, especially in preventing violence against them, most notably with the UN's UNITE campaign launched in 2008. The efforts first began nearly 30 years ago with the Convention of Belén do Pará in 1994 (OAS [2009]), formally the Inter-American Convention on the Prevention, Punishment and Eradication of Violence against Women. As a result of this conference, 24 of the 33 Latin American countries enacted a "first wave" of gender policies, ratifying the outcomes of the convention (Essayag [2017]). Colombia had a leading rate of IPV in Latin America and the world (García-Moreno, Claudia et al. [2013]) [2] , prompting its government to pass Law 294 in 1996 (Colombia Government [1996]), formally recognized domestic violence as a crime, and initiated protections for affected family members. After the

[2] The average incident rate of domestic violence in the world and Americas in 2012 was about 30%, with a 95% CI in Americas of 25.8 to 33.9. In 2010, Colombia's rate was 37%, and at 32% in 2015, was still above that average (Profamilia [2011] and Profamilia [2015])

UNITE campaign, it (and many other Latin American countries) passed stronger legislation in 2008 and 2011 to further protections specifically for women and other victims of violence in general (Essayag [2017]). One example of this was Law 1257, which improved support for victims of domestic violence in the legal system and protections while going through the process. It also strengthened penalties for domestic violence offenses, and made it easier to prosecute abusers, in part by making it easier and safer to report incidents[3]. Since then, the national government also announced plans and follow-ups in 2010 and 2015 with goals to reduce IPV (Santos [2014] and Santos [2018]).

Law 1257 was formally adopted December 2008, and the mandate to local governments sent out accordingly. The rollout in departments was not on a strict timeline; while local governments do have a direct tie to the higher regional or national level, they also have great autonomy in when and how they implement decrees (Hudson and of Congress [2010]). Only two departments implemented the policy before 2008, Antioquia (2002) and Bogotá, DC (2004) (Gobierno de Chocó [2017] Gobierno de Chocó, 2017). I say that a department implemented the law or policy if they instituted a gender policy in their department, and/or have strong institutional gender equality as measured by the AECID [2011] report.

1.3 Data and Empirical Methodology

1.3.1 Data

I use data from the individual level survey of the Demographic Health Survey (DHS) waves V to VII (2005, 2010, and 2015) for both household and individual surveys. No earlier waves are used because of inconsistency regarding inclusion of outcome and control variables. The DHS is a cross-sectional survey conducted in countries worldwide, with a standard questionnaire common to all countries, and additional local questions specific to each. In Colombia, the organization PROFAMILIA conducts the survey locally every five years. It uses the standard

[3]Translation of objective Law 1257: The law has as its objective the adoption of norms that guarantee all women a life free of violence, in the public as in the private sphere, the practice of recognized rights in the domestic and International legal system, the access to all administrative and judicial procedures for their protection and attention, and the adoption of the public policies necessary for their realization.

survey in Colombia, as opposed to a continuous model (conducted every year) employed in other countries. While the samples are nationally representative, I include sample weights as recommended by DHS to ensure accurate interpretation of the results.

The survey has a total of 133,583 individual female observations (individual-year) across all three waves. To construct the sample used in the analysis, I drop all observations missing any of the six outcome variables (see Table 1.3.3), leaving 75,478 observations. After excluding missing values for control variables, the final sample for the regressions is 69,128 observations. I exploit the variation in the timing of policy implementation to tease out the true effects of the policy on the bargaining outcome variables. While the law (Ley 1257) was passed in 2008, it did not require immediate implementation by the departments. Therefore, the departments have slowly implemented it over the course of several years. The staggered roll-out means that I am comparing women in a department (geographic district) in which the policy has been implemented locally to those in a department where the policy has not yet been implemented. I take 2005 and 2010 to be base years, or years pre-policy implementation. The control group then becomes departments where no policy is implemented between 2010 and 2015, while the treatment group are departments that do implement a gender policy by 2015.

I define "implementation" as the creation of a gender policy that promotes a reduction in violence against women, and creation of governmental offices to oversee programs that support this goal. Along with policies to reduce violence against women, as AECID [2011] also considers establishing women in higher roles in government as part of this policy, I include this criteria as well.

I use two separate sources to determine implementation year, AECID [2011] report and Gobierno de Chocó [2017] report. I use the AECID [2011] report as the source for the primary results, and the Gobierno de Chocó [2017] report in conjunction with the AECID [2011] report as a robustness check (see 1.4.1).

The relationship status of the respondent is accounted for in the controls used in the regressions, and includes those who are legally married and those in a long-term union with their partner.

Issues for Identification

The main issue for identification is the timing of the adoption of a gender policy, a choice likely to depend on characteristics of the implementing department. It could be that early adopting departments are wealthier, have a different rate of IPV, higher population, or other characteristics. To mitigate these potential discrepancies in resources between departments and over time, I include department-level fixed effects and year fixed effects.

Testing for Balance

To investigate if there is balance between the treatment and control groups, I report summary statistics for both covariate and outcome variables by group (see Tables 1.3.1 and 1.3.3). For the control variables, the treatment has about half the number of observations as the control group for both periods, with 17,830 versus 34,545 in the pre-period and 5,682 versus 11,071 for the post-period. The average age for the women in the sample is slightly higher for both periods in the treatment group ("Gender Policy") by less than half a year (0.42 - 0.47), starting just under 33 years, and ending just over 34 years. This group also has slightly fewer total children born to them, closer to 2 rather than 2.3 in the control group; however, both groups are nearly identical in the percentage of women who have ever had any children.

Overall, the education levels for both groups are comparable at the lowest and highest levels, with the treatment group being slightly more concentrated at secondary school attainment, and the control group more so at primary school as the highest attainment.

Those in the treatment group are also nearly ten percent more likely to live in urban areas, suggesting that the departments implementing gender policies are less rural than those that have not implemented them. The wealth quintiles[4] distribution show a higher concentration of the control group at lower levels, with over 50 percent falling in the "poorest" or "poorer" classifications, while the treatment group departments have the majority in the "middle" or higher groups. These findings suggest that the departments that have not implemented

[4]The wealth quintile variable is used as a proxy for income and household resources, which are not directly provided in the survey.

gender polices are not only more rural, but also less resource-rich.

The outcome variables (Table 1.3.3) are the six bargaining variables which indicate if the respondent has sole final say regarding the listed topic. I see the treatment group is slightly more likely to have final say over their own healthcare, but that both groups see a decrease between the pre- and post-periods. In fact, for all outcomes except final say on spending their own earnings, the percent of respondents who have final say decreases from the pre- to post-period for both the treatment and control groups. The treatment group also is slightly more likely to have final say over spending their own earnings inn both periods. The rest of the outcome variables are not consistently higher for one group over the other across both periods, and all except the pre-period for visits to family and the post-period of what to cook daily are within one or two percentage points of each other. Regarding the exceptions, the former has the control group as five percent more likely to have final say, and the latter has the treatment group as four percent more likely to have final say.

Table 1.3.1: Summary Statistics for Control Variables with Mean Differences

	Pre-Period (2005, 2010)			Post Period (2015)		
	Gender Policy	No Gender Policy	Mean Difference	Gender Policy	No Gender Policy	Mean Difference
Age of	33.60	34.13	-0.53^{***}	33.73	34.20	-0.46^{**}
Respondent	(8.57)	(8.63)	(0.09)	(8.68)	(8.62)	(0.14)
Total Number of	2.61	2.29	0.31^{***}	2.40	2.12	0.29^{***}
Children Ever Born	(1.84)	(1.56)	(0.02)	(1.72)	(1.46)	(0.03)
Had Any	0.92	0.92	0.01	0.92	0.91	0.01^{*}
Children	(0.27)	(0.28)	(0.00)	(0.28)	(0.29)	(0.00)
Lives in	0.71	0.82	-0.11^{***}	0.73	0.80	-0.07^{***}
Urban Area	(0.46)	(0.39)	(0.00)	(0.45)	(0.40)	(0.01)
Type of Union	0.33	0.40	-0.07^{***}	0.28	0.35	-0.07^{***}
	(0.47)	(0.49)	(0.01)	(0.45)	(0.48)	(0.01)
Education Level						
No Education	0.03	0.02	0.02^{***}	0.03	0.01	0.01^{***}
	(0.18)	(0.14)	(0.00)	(0.16)	(0.11)	(0.00)
Primary	0.33	0.28	0.05^{***}	0.25	0.20	0.05^{***}
	(0.47)	(0.45)	(0.00)	(0.43)	(0.40)	(0.01)
Secondary	0.45	0.50	-0.05^{***}	0.43	0.49	-0.05^{***}
	(0.50)	(0.50)	(0.01)	(0.50)	(0.50)	(0.01)
Higher	0.18	0.20	-0.02^{***}	0.29	0.30	-0.01
	(0.39)	(0.40)	(0.00)	(0.45)	(0.46)	(0.01)
Wealth Quintiles						
Poorest	0.26	0.11	0.15^{***}	0.30	0.14	0.16^{***}
	(0.44)	(0.32)	(0.00)	(0.46)	(0.35)	(0.01)
Poorer	0.29	0.20	0.09^{***}	0.34	0.25	0.09^{***}
	(0.45)	(0.40)	(0.00)	(0.47)	(0.43)	(0.01)
Middle	0.21	0.23	-0.02^{***}	0.20	0.23	-0.03^{***}
	(0.41)	(0.42)	(0.00)	(0.40)	(0.42)	(0.01)
Richer	0.14	0.23	-0.09^{***}	0.11	0.21	-0.10^{***}
	(0.35)	(0.42)	(0.00)	(0.32)	(0.41)	(0.01)
Richest	0.09	0.22	-0.13^{***}	0.05	0.17	-0.12^{***}
	(0.29)	(0.41)	(0.00)	(0.23)	(0.38)	(0.01)
Observations	25493	13185	38678	11071	5682	16753

Note: Wealth quintile categories as indicated. Standard deviations reported for each mean, standard errors reported for differences. Treated group is "Gender Policy", control group is "No Gender Policy".

Table 1.3.3: Summary Statistics for Outcome Variables with Mean Differences

	Pre-Period (2005, 2010)			Post Period 2015		
	Gender Policy	No Gender Policy	Mean Difference	Gender Policy	No Gender Policy	Mean Difference
Own Healthcare	0.73	0.80	-0.07^{***}	0.72	0.76	-0.04^{***}
	(0.44)	(0.40)	(0.00)	(0.45)	(0.43)	(0.01)
Large HH Purchases	0.25	0.25	-0.00	0.23	0.22	0.01
	(0.43)	(0.43)	(0.00)	(0.42)	(0.42)	(0.01)
Daily HH Purchases	0.44	0.44	0.00	0.37	0.39	-0.02^{**}
	(0.50)	(0.50)	(0.01)	(0.48)	(0.49)	(0.01)
Visits to Familiy	0.33	0.30	0.03^{***}	0.29	0.28	0.01
	(0.47)	(0.46)	(0.00)	(0.45)	(0.45)	(0.01)
What to Cook Daily	0.70	0.71	-0.01	0.61	0.65	-0.04^{***}
	(0.46)	(0.45)	(0.00)	(0.49)	(0.48)	(0.01)
Spending Own	0.80	0.82	-0.02^{***}	0.65	0.69	-0.04^{***}
Earnings	(0.40)	(0.38)	(0.00)	(0.48)	(0.46)	(0.01)
Observations	25493	13185	38678	11071	5682	16753

Note: All variables are for the Respondent (R) having final say for that outcome. Standard deviations reported for each mean, standard errors reported for differences.

1.3.2 Empirical Methods

I use a difference-in-difference (DiD) estimation strategy to examine the pre- and post-periods of the law. As in Durevall [2021], I exploit the variation in the adaptation of gender policies by the 33 departments and Bogotá, D.C., with the main treatment variable being whether the department is forming a gender policy by 2010, and implemented said policy by 2015. For the treatment group, I first focus on those departments recognized by AECID [2011] as having strong gendered institutions, measured by number of women leading government departments, gender policies, and actions to promote gender equality. Given this, there are ten departments fitting the criteria, with two (Magdalenda and Caquetá) having gender policies in formation. I first use only the eight departments from AECID with high gender institutionally and fully formed gender policies, then add in the two departments with gender policies in formation. Last, I add in departments identified by the report from the Gobierno de Chocó [2017] as having implemented a gender policy for violence against women prior to 2015. The main DiD regression is specified as

$$Y_{idt} = \beta_0 + \beta_1(Post_t * Policy_d) + \beta_2 X_{idt} + \gamma_d + \eta_t + \varepsilon_{idt} \tag{1.1}$$

with Y_{idt} representing the outcome for respondent i in department d in survey year t. The $Post_t$ variable is an indicator equal to 1 if the survey year is 2015, and 0 otherwise. The "treatment" variable is represented by $Policy_d$, an indicator equal to 1 if the department is included as "treated", i.e., if the department has a gender policy implemented by 2015, and 0 otherwise. Individual controls are included in X_{idt}, γ_d represents department-level fixed-effects, μ_t the year fixed-effects, and ε_{idt} the error. The main coefficient of interest is β_1, showing the impact of the implementation of a gender policy on household bargaining outcomes. The regressions all use the DHS sample weights at the individual level. The individual and household control variables are age, ethnicity, wealth level, education level and number of years of education, number of children, urban or rural residence, employment status, and relationship status (currently married or living with a partner).

While the outcome variables representing various types of bargaining power are those listed in Table 1.3.3, I use principle component analysis (PCA) to construct an index from these variables, and use the resulting component as the main outcome variable in the results. To construct this index, I first create a correlation matrix of the bargaining power variables (Table 1.3.5). This first step determines if there is enough of a link between the potential index variables to proceed with the process. While some correlations seem negligible, the majority are greater than 0.24, suggesting that the grouping is valid. I then run the PCA analysis and plot the result in a scree plot (Figure 1.1). The scree plot graphs the eigenvalues of each component, with a line at one to illustrate which are above the threshold for inclusion. From the graph, I see that the first two components are above this threshold; however, as the eigenvalue of the first component is just over double the value of the eigenvalue of the next component (2.261 and 1.041), I include only the first component.

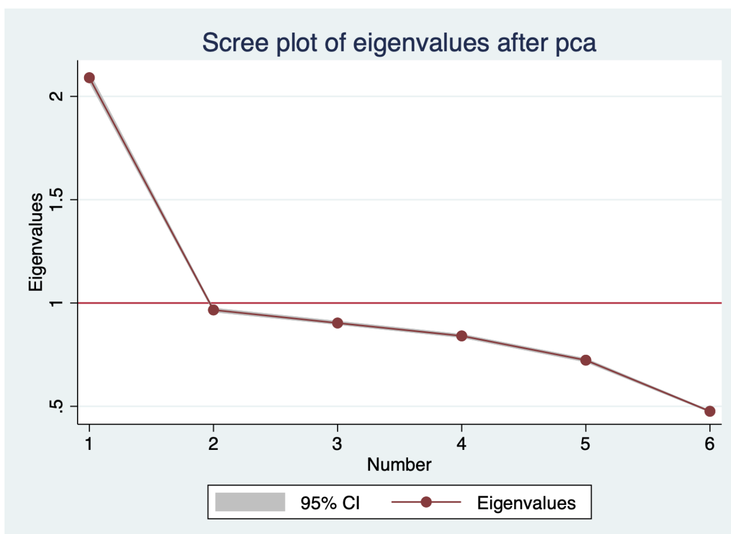


Figure 1.1: Scree Plot for Respondent has Final Say PCA

Note: Scree plot from principle component analysis of all outcome variables

Table 1.3.5: Correlation of Outcome Variables For Respondent Only with Final Say

	Own Healthcare	Large HH Purchases	Daily HH Purchases	Visits to Familiy	What to Cook Daily	Spending Husband's Earnings	Spending Own Earnings
Own Healthcare	1.000						
Large HH Purchases	0.346	1.000					
Daily HH Purchases	0.363	0.672	1.000				
Visits to Familiy	0.353	0.462	0.414	1.000			
What to Cook Daily	0.293	0.350	0.484	0.245	1.000		
Spending Husband's Earnings	0.060	0.081	0.102	0.026	0.092	1.000	
Spending Own Earnings	0.247	0.120	0.193	0.099	0.240	0.177	1.000

Note: Correlation matrix of all outcome variables, for use in principle component analysis

Testing for Pre-Trends

To test for pre-trends, I include an event-study analysis in Figure 1.2. I regress the resulting variable from the PCA on each year of the data, including the same controls and fixed effects as in the main specifications and with year 2010 as the baseline. I use a categorical variable of the years so that they are all included in one regression, rather than regressing the PCA variable on each year separately. The coefficients are then plotted in the graph 1.2, which shows that while the coefficients for 2005 and 2015 are slightly below and above zero (the baseline) respectively, they are not significant. In particular, the insignificance of the coefficient for year 2005 suggests a lack of pre-trends between the treatment and control groups when including department fixed effects and controls (see 1.3.1 for list). This shows no real change between the pre-periods, and slight change in the post period. The process is repeated for each element of the index in figures A1, and shows no evidence of trends in the pre-periods for all variables.

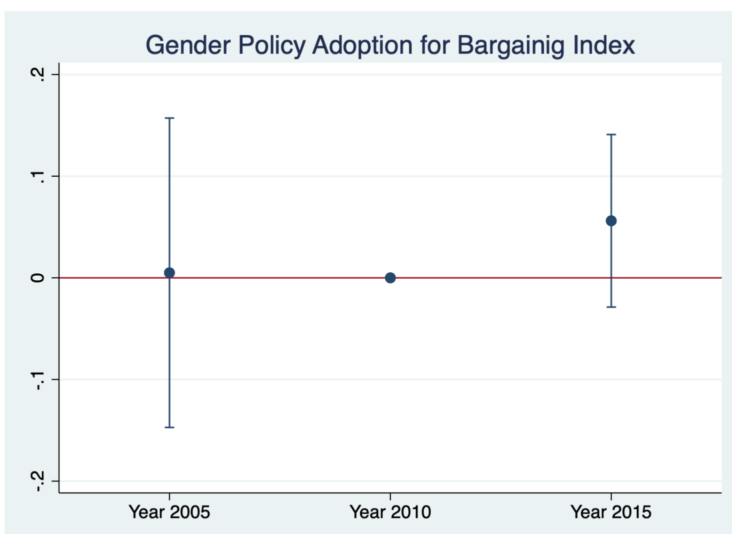


Figure 1.2: Event Study

Note: Coefficients from regression with fixed effects and controls, plotted. Year 2010 is baseline.

The t-test for the pre-trends regression shows a t-statistic of -0.50, with coefficient -0.0571 and standard error 0.1134. The coefficient is not significant at conventional levels, implying a lack of evidence of pre-trends.

1.4 Results

I find evidence of an increase in women's bargaining power from Law 1257 (1.4.1). Five out of the seven results have positive coefficients with four significant at the ten or five percent level, and only one is negative and significant. A positive coefficient means that after the implementation of a gender policy in a department, a female respondent is more likely to report that they have sole final say for that particular topic. The four significant coefficients are *Visiting Family and Relatives*, *What to Cook Daily*, *Spending Own Earnings*, and the PCA for the overall bargaining index. The results are significant at the ten percent level for all but *Visiting Fmaily*, which is significant at the five percent level. From left to right, the positive significant coefficients represent a 11.9%, 7.9%, 3.2%, and a 190.8% increase from the mean, respectively. The two negative results are *Own Healthcare* with a significant 7.0% decrease from its mean, and *Large Household Purchases*, where the -0.00614 coefficient represents a 2.5% decrease from its mean. While two coefficients are negative, the majority, including the indexed PCA variable, are positive and significant. The negative and significant *Own Healthcare* could indicate a separate issue, and is not strong enough to outweigh the other factors in the PCA. Therefore, I conclude there is evidence supporting a positive relationship between the law and women's bargaining power in the household.

Most notably, I see these effects despite several data limitations. First, there are only three years of cross-sectional data available, since the survey is only conducted every five years. Second, the number of individuals is also limited, with only 69,128 for the entire final sample, and less than 17,000 for the final year (2015). These limitations mean that effects could be underestimated since they may not accurately represent the population, and reduce the statistical power of the model. Additionally, the small number of departments, combined with the necessity of clustering at that level, further reduces the statistical power. However, I still see weakly positive effects with most coefficient signs as positive, and for the two that are negative, they are both insignificant and are a small percentage change from their respective means.

Table 1.4.1: Respondent has Sole Final Say on Decision Outcomes with Fixed Effects

	(1) Own Healthcare	(2) Large HH Purchases	(3) Daily HH Purchases	(4) Visiting Family	(5) What to Cook Daily	(6) Spending Own Earnings	(7) Principle Component
Post x Policy	-0.0541**	-0.00614	0.0174	0.0351**	0.0546*	0.0250*	0.0540*
	(0.0225)	(0.0107)	(0.0111)	(0.0128)	(0.0271)	(0.0145)	(0.0302)
N	55431	55431	55431	55431	55431	55431	55431
Mean of Y	0.769	0.242	0.433	0.296	0.691	0.770	0.0283
Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. "HH" indicates "household". Standard errors (in parenthesis) are clustered by department, and results also have department and year fixed effects. Data is from the Demographic Health Survey for Colombia, waves V to VII (2005, 2010, 2015). Controls include respondent's age, wealth quintile, urban or rural living environment, level of education by school level, number of kids, marital status, and employment status.

1.4.1 Heterogeneity and Sensitivity Analyses

It is reasonable to suspect that there could be differences between the effect of the law on those with high levels education and those with little to no education. Indeed, tabulating the responses for the bargaining power index components by education level reveals differences across groups, especially for power over your own healthcare (83.42% of the highest educated report this, compared to only 61.52% of the lowest educated group). It could be that this difference is seen in the index as a whole, or that it is concentrated in this particular measure. However, when I run the regressions for each education level for the PCA bargaining index, the results are null for the lowest and secondary education groups, and significant for the primary school and highest educated group (see Table 1.4.2). As the highest educated group likely had the most power to start with, it could be that the minuscule increase from the gender policy was enough to push the rest of the group into power. Since the lowest level of education group has such a large gap in power to overcome, the bargaining power gained from the gender policies was not enough to surmount this difference. The primary school group could be at a threshold, where the gap is not quite as large as the lowest education group, and they are likely to benefit from any small changes. In the original PCA regressions, it shows that all levels are positive relative to the base level of no education; the coefficient for primary education is significant at the five percent level and the other two are significant at the one percent level. When the variable is not split into categories, it is positive and significant at the one percent level as well, suggesting the true relationship between education and the PCA is that bargaining power increases with education, as expected. This concurs with the original results, and further strengthens the argument of a weakly positive relationship between the adoption of a gender policy and bargaining power within the household.

An important source of contention could be the definition of the "treatment" group, and which districts it includes. According to the AECID document (AECID [2011]), the criteria are the adoption of a gender policy and institutional measures such as the number of women holding various government offices. This document also lists if a department has a policy in development, a group excluded from the specification above. However, I could also include just the adoption of any type of gender policy with protections for violence against women, as listed in the Government of Chocó document. Therefore, I run two additional variants of the treatment group for the main specification. The first includes all departments listed in the

AECID that have either already implemented a gender policy, or have one in development. The second includes all of these departments with the addition of departments listed in the other document as having implemented a gender policy before 2015. The AECID specification, table 1.4.3, shows results similar to the original, with all coefficients showing the same signs and magnitudes, and three of the same coefficients being significant. However, table 1.4.4 shows that the expanded specification now has no significant coefficients. From the initial specification to AECID to the most inclusive, the percentage of 33 departments in the treatment group are 24.24%, 33.33%, and 48.48% respectively. All are within the desired range; however, it may be that the most inclusive specification shows no effects because either there are too many departments included, or there is too large of a difference between the treatment and control.

Table 1.4.2: PCAs by Education Level

	(1) No Education	(2) Primary Only	(3) Secondary Only	(4) Higher Education
Post x Policy	0.0368	0.120**	-0.00596	0.107*
	(0.155)	(0.0480)	(0.0448)	(0.0608)
N	1489	15973	25688	12280
Mean of Y	-0.0537	-0.0209	0.0704	0.00625
Fixed Effects	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. "HH" indicates "household".

Table 1.4.3: Decision Outcomes - AECID

	(1) Own Healthcare	(2) Large HH Purchases	(3) Daily HH Purchases	(4) Visiting Family	(5) What to Cook Daily	(6) Spending Own Earnings	(7) Principle Component
Post x Policy	-0.0502**	-0.00639	0.0141	0.0282*	0.0503*	0.0163	0.0388
	(0.0245)	(0.0104)	(0.0119)	(0.0152)	(0.0255)	(0.0150)	(0.0347)
N	55431	55431	55431	55431	55431	55431	55431
Mean of Y	0.769	0.242	0.433	0.296	0.691	0.770	0.0283
Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. "HH" indicates "household". Standard errors (in parenthesis) are clustered by department, and results also have department and year fixed effects. Data is from the Demographic Health Survey for Colombia, waves V to VII (2005, 2010, 2015). Controls include respondent's age, wealth quintile, urban or rural living environment, level of education by school level, number of kids, marital status, and employment status. Treated group includes those departments designated by AECID as having a gender policy in place or in progress by 2015.

Table 1.4.4: Decision Outcomes - AECID and Chocó

	(1) Own Healthcare	(2) Large HH Purchases	(3) Daily HH Purchases	(4) Visiting Family	(5) What to Cook Daily	(6) Spending Own Earnings	(7) Principle Component
Post x Policy	-0.0421	0.00656	0.0163	-0.0134	0.0378	0.0247	0.0197
	(0.0289)	(0.0113)	(0.0177)	(0.0170)	(0.0240)	(0.0158)	(0.0437)
N	55431	55431	55431	55431	55431	55431	55431
Mean of Y	0.769	0.242	0.433	0.296	0.691	0.770	0.0283
Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. "HH" indicates "household". Standard errors (in parenthesis) are clustered by department, and results also have department and year fixed effects. Data is from the Demographic Health Survey for Colombia, waves V to VII (2005, 2010, 2015). Controls include respondent's age, wealth quintile, urban or rural living environment, level of education by school level, number of kids, marital status, and employment status. Treated group includes all departments designated by AECID as having a gender policy in place or in progress by 2015, plus those indicated by the Gobierno de Chocó report as having a policy in place by 2015.

1.5 Conclusion

From my analyses, I find weak evidence for a positive relationship between the implementation of a gender policy in a department and an increase in bargaining power for women in the household. This is for both respondents currently in a relationship, and those who are not. The two elements of bargaining power that exhibited significant effects were visiting family and relatives, and deciding what to cook daily. These two, particularly the last, can be seen as traditionally female roles; thus, it may be that the law shifted the cultural norms by starting with those elements already in a female role. As these effects are seen despite a lack of data, I would recommend this to further study with additional or alternate data sources.

One may intuitively expect spillovers given the policy changes empowering women, and this work provides the first evidence for that in Colombia with domestic violence legislation. The original estimates for improving women's lives from this law are underestimated, as they did not account for the spillover into household bargaining. Future policy work should not only account for the direct target of its work, but also potential spillovers, to accurately assess the impact of it on bargaining power. These findings are also important for crafting future policy, as it can be hard to target aspects that directly influence household or other types of bargaining power. This paper shows that certain legislation can indirectly affect these issues that can be hard to get at, even if only a little. Future policy (and future research) can work on creating ways to increase the strength of these spillover connections.

It may be useful to know if a respondent's current household structure was in place before the adoption of the gender policy in their department. If the status quo of the household had already been established, it would likely take longer to change after the policy as compared to someone entering a new household structure after the policy, when a new dynamic could easily be established. For further research, I will conduct a similar study looking only at those in relationships, and ideally those whose relationship status changed after the policy to account for this element.

Chapter 2

Differential Impact of Economic Downturns on Labor Market Outcomes Across Personality Types

Rachel Inafuku and Maya Ward

2.1 Introduction

Pop culture quizzes claim to be able to choose your optimal career path and give you a glimpse of what your future holds based on your personality. While these quizzes may be strictly for entertainment, previous studies have shown that personality traits do in fact influence various career outcomes. In typical wage models, earnings are determined by human capital, which consists of a set of skills that contribute to a worker's level of production. These skills are often characterized by observable characteristics such as education, work experience, age, gender, etc.; proven to influence earnings. Nevertheless, there is still a large amount of variation between individuals of similar observable traits, indicating that unobservable characteristics must be missing to at least partially explain the variation. This means that economists ignore a potentially important determinant of labor market success: personality traits.

In this study, we fill the gap in the literature by looking at the impact economic downturns on labor market outcomes across the Big Five[1] personality traits (extroversion, agreeableness, openness, emotional instability, and conscientiousness), using data from the National Longitudinal Survey of Youth '97 cohort (NLSY). Specifically, we exploit the variation caused by business cycle fluctuations to assess the impact on income, employment, and unemployment insurance take up amongst young adults, and if it varies across the Big Five traits. While several studies in the psychology literature have looked at the relationship between personality traits and various labor market outcomes, personality traits are not as commonly used in studies by economists. Economists tend to leave out this potentially important factor of labor market outcomes. Moreover, because the literature uses a variety of personality measures in their studies, not all personality findings are directly comparable. Even studies which specifically focus on the Big Five personality traits find slightly differing results from one another because of the differences in the data used [Caliendo et al., 2014], definitions of personality traits, and the cultural context [Borghans et al., 2008]. Not only does this paper contribute to a greater understanding of the Big Five traits on labor market outcomes, but it also addresses an important hole in the literature in which economists tend to ignore.

In economics, most of the personality literature is based off of work by Bowles et al. [2001], where they find that noncognitive traits (i.e., attitudes, work ethic, etc.) affect both earnings and the generational transmission of economic status. Several studies both in the US and abroad found different relationships between personality and labor market outcomes across gender. Heineck and Anger [2010], using the BHPS for UK individuals, found that there is a positive relationship between openness and wages, and a negative relationship between agreeableness and wages for both genders. The negative relationship between neuroticism (emotional instability) and wages were specifically driven by women. Similarly, Mueller and Plug [2006] found a negative association between agreeableness and earnings for men and a positive association for openness. Women appear to get a wage premium for openness and conscientiousness. Duckworth and Weir [2010], using the HRS, focus on conscientiousness and its interaction with other traits, but also find that it has an overall positive effect on lifetime earnings and retirement savings, although the influence is different for males and females within a couple. Nabeshima and Seay [2015] also use the HRS and find that extroversion and conscientiousness are positively associated with net worth, while agreeableness

[1]See Digman [1990] and Goldberg [1993] to learn more about the Big Five personality traits

is negatively associated with wealth accumulation.

A potential barrier to using personality traits in an empirical model is endogeneity that may invalidate the causal effect of traits on labor market outcomes. For example, if personality traits tend to fluctuate over time, it could be the case that labor market outcomes influence an individual's personality. However, if traits are given and stable over time, we can ignore this potential confounding issue and assume that traits are independent of labor market outcomes in our model. Indeed, we (and many in psychology) choose to look at the Big Five for this reason. The theory is that once formed in childhood, these traits are then immutable or innate, and can be taken as a characteristic of the individual, such as gender, race, or ethnicity (Digman [1990] and Goldberg [1993]). Cobb-Clark and Schurer [2012] finds that while the Big Five traits are not literally fixed, they are stable for working-aged adults over a four year period. When specifically looking at economic outcomes, they find that having at least five adverse employment or income related events decrease emotional stability by a minimal amount. Rantanen et al. [2007] also find that the Big Five are not fixed, but relatively stable for working-age adults between ages 33 and 42. Using panel data and structural equation modeling, they examine the stability across gender and find that traits remain stable for both sexes.

For our empirical analysis, we use data from the National Longitudinal Survey of Youth 1997 Cohort (NLSY). The NLSY is a longitudinal panel data set that began interviewing about 9,000 youths ages 12 through 17 in the year 1997 and now conducts the survey biennially. Data included in the survey spans across various demographic traits, health outcomes, career variables and more. The survey also includes questions pertaining to various personality traits. We specifically focus on working aged adults from the survey waves 2000-2011, 2013, and 2015. Thus, our sample consists of those ages 18 through 36 years old.

We find that those with higher levels of emotional instability tend to see larger unemployment insurance take up and fewer weeks of employment during recessions relative to those who are more emotionally stable. Negative effects of labor market outcomes during economic downturns for those with higher levels of emotional instability are primarily driven by females. This finding is in line with Heineck and Anger [2010]. Additionally, the effects do not seem to be driven by employer discrimination. Instead, workers with higher levels of emotional instability may be less productive during recessions.

2.2 Data

2.2.1 National Longitudinal Survey of Youth

The National Longitudinal Survey of Youth (NLSY) 1997 cohort is an individual panel survey, conducted since 1997, that consists of 9,000 American youths. Individuals in the survey were born between the years 1980 and 1984. The survey has been administered 18 times thus far. For this study, we use survey data from the years 2000-2011, 2013 and 2015. We drop youths who are younger than 18 years old to focus specifically on working aged adults. Thus, our sample consists of adults ages 18 through 36 years old. Our outcome variables include the log of an individual's total income in wages, salary, commissions or tips in the past year, the number of weeks an individual was an employee on a roster in a year, and a dummy variable equal to 1 if an individual collected unemployment insurance for at least one month in a year. In order to keep discouraged workers in our data, we keep individuals who reported a total annual income of zero dollars. Thus, we add a dollar to each individual's total income before taking the log.

2.2.2 Bureau of Labor Statistics

We use the monthly regional unemployment rate as our indicator for the business cycle. The Bureau of Labor Statistics (BLS) reports unemployment statistics for various geographies across the US monthly. The unemployment rate is estimated using data collected from the Current Employment Statistics, a monthly survey which contains approximately 140,000 businesses and government agencies drawn from 9 million unemployment insurance tax accounts.

2.2.3 Summary Statistics

We display summary statistics of our data in Table 2.2.1. The top panel of the table describes data on the Big Five traits. Each trait is constructed by taking the average of various personality attributes related to one of the Big Five categories. We explain more about the construction of these Big Five variables in section 2.3.1. For each trait, the sample ranges from 1 to 7 where a 7 indicates that the trait strongly applies to an individual. Sample means for openness and conscientiousness are the highest out of all the Big Five traits with respective values of 5.47 and 5.21, indicating that on average the individuals in our sample feel that they are more open and conscientious. Our sample identifies least with emotional instability with a sample mean of 3.04.

Our data consists of adults ages 18 through 36. The mean age is just under 25 years old. Thus, our study focuses on the young adult population. About a quarter of the individuals in our sample are students who are enrolled in a high school, 2-year college, 4-year college or graduate degree program. Annual income (total wages, salary, tips, and commissions) is about $24,000 in nominal terms. The relatively low mean income reflects a younger group of working individuals who are likely early career starters. Moreover, the mean number of weeks employed in a year is just under 38 weeks and approximately 5% of the sample collected unemployment insurance for at least one month in a year. Since pregnant women may be subject to differential labor market conditions [Budig and England, 2001], we eliminate them from our sample. We also eliminate those who are active members of the armed forces, resulting in 8,699 unique individuals in our data.

Table 2.2.1: Summary Statistics

	Mean	Std. Dev.
Big Five Traits		
Extroverted	4.65	1.36
Agreeable	4.40	1.66
Open	5.47	1.10
Emotionally Unstable	3.04	1.33
Conscientious	5.21	0.84
Other		
Female	0.49	0.50
Age	24.84	4.35
Annual Income	24,080.71	23,216.45
Weeks Employed	37.58	19.25
Received Unemployment Insurance	0.05	0.22
Unemployment Rate	6.34	1.85
Attended College	0.21	0.41
Student	0.24	0.42
White	0.57	0.49
Black	0.28	0.45
Other Race	0.15	0.36
Number of Children	1.46	1.09
Married	0.23	0.42
Urban Residence	0.81	0.40
ASVAB Test Score	45,490.42	29,436.85

Data is from the NLSY 1997 Cohort from survey years 2000-2011, 2013 and 2015. Personality traits are self-reported on a scale of 1 through 7 where 7 indicates the trait strongly applies to the individual. Annual income is reported in US dollars. ASVAB Test Scores are age-adjusted math and verbal test scores. N represents the number of individuals in the sample.

2.3 Methodology

Using data from the NLSY, we analyze the effect of business cycle downturns on income, weeks of employment, and unemployment insurance collection, and how they vary across personality traits.

2.3.1 Constructing the Big Five Personality Traits

We construct measures of personality based on the Big Five personality traits. The NLSY survey consists of several traits in regards to the respondent's personality. Respondents are asked to rate each trait on a scale from 1 to 7 where a higher value indicates that the trait strongly applies to the individual and vice versa. To replicate the Big Five in our sample, we first categorize all relevant personality trait variables into groups that correspond to each of the Big Five traits. We display these groupings in Table B2. We also take personality traits from the survey that correspond to the *opposite* of one of the Big Five traits and invert their scales so that a 1 indicates that the statement strongly applies to the individual and a 7 indicates that the trait does not apply to the individual. For example, the question asking directly about being extroverted and enthusiastic uses the normal scale, while that asking the opposite, if the respondent is reserved and quiet, has the scale inverted so that a higher score still indicates more extroversion. We then place these attributes from the NLSY with inverted scales in their respective the group that corresponds to one of the Big Five traits. While most survey questions pertaining to personality traits are conducted once over the entire sample period, survey questions that correspond to hard working and a rule following attributes are conducted in two survey waves (2008 and 2010). For these traits, we construct one time-invariant variable for each trait by taking the average values from the 2008 and 2010 survey waves. After grouping each attribute into one of the Big Five traits and implementing necessary scale inversions, we take the average of all trait(s) within their respective groupings. We display histograms of the constructed Big Five traits in Figure B1.

2.3.2 Empirical Methodology

Our main specification is as follows:

$$Y_{irt} = \beta_0 + \beta_1 Trait_i + \beta_2 UR_{rmt} + \beta_3 Trait_i * UR_{rmt} + \gamma X_{irt} + \delta_j + \nu_r + \tau_t + \mu_m + \epsilon_{irt}$$

where Y_{irt} is the dependent variable for individual i residing in region r in year t. The outcome variables we analyze in this study are the log of annual income, number of weeks employed in a year, and a dummy variable equal to 1 if the individual received unemployment insurance for at least one month in a year. The variable, $Trait_i$ is one of the Big Five personality traits standardized. We standardize traits by subtracting the mean and dividing by the standard deviation. The variable, UR_{rmt}, is the de-meaned unemployment rate reported in percentage points for region r in interview month m of year t. The term X_{irt} is the vector of controls including gender, age and its square, race, highest level of education, marital status, an urban residence indicator, student enrollment status, number of biological children, and age-adjusted ASVAB test scores. The terms, δ_j, ν_c, τ_t, and μ_m are occupation, region, interview year, and interview month fixed effects respectively. Standard errors are clustered at the region-year level.

It is important to note that due to data limitations, we only have one time period of observations for our dependent variable $Trait_i$. Thus, for our identification strategy we must rely on the assumption that personality traits are time invariant. We discuss this in section 2.5.1. Because personality is time invariant in our sample, we do not use individual fixed effects in our baseline specification [2]. However, we include each individual's age-adjusted Armed Services Vocational Aptitude Battery (ASVAB)[3] test scores in our vector of covariates X_{irt}, which allows us to control for unobserved ability and intelligence that may impact labor market outcomes and would otherwise have been controlled for using individual fixed effects.

[2] In future research, we plan to include them and explore the trade-off between identifying the interaction, and the potential precision lost

[3] The ASVAB test is an aptitude test developed and maintained by the Department of Defense that is conducted at over 14,000 schools nationwide. The NLSY adjusts ASVAB scores by 3-month age brackets.

2.4 Results

We first report the correlation between each personality trait with our outcome variables in Table 2.4.1. Extroversion has a strong positive correlation with better labor market outcomes across all three dependent variables. Those who are more agreeable tend to see lower income. This finding is in line with Heineck and Anger [2010] and Mueller and Plug [2006]. On the other hand, conscientiousness has a positive relationship with income. Emotional instability is associated with lower income and fewer weeks of employment in a year. Moreover, openness is negatively correlated with collecting unemployment insurance.

Table 2.4.1: The Correlation Between the Big 5 Personality Traits and Labor Market Outcomes

	(1)	(2)	(3)
	Log of Income	Weeks Employed	Unemployment Insurance
Extroverted	0.070***	0.566***	–0.004**
	(0.008)	(0.096)	(0.002)
Agreeable	–0.029***	–0.033	0.001
	(0.011)	(0.115)	(0.002)
Open	0.028**	0.093	–0.001
	(0.012)	(0.118)	(0.002)
Emotionally Unstable	–0.024**	–0.801***	0.002
	(0.010)	(0.113)	(0.002)
Conscientious	0.058***	0.980***	–0.001
	(0.010)	(0.096)	(0.002)
Males			
Extroverted	0.086***	0.725***	–0.003
	(0.013)	(0.162)	(0.003)
Agreeable	–0.053***	–0.497***	0.001
	(0.015)	(0.155)	(0.002)
Open	0.005	0.027	0.000
	(0.014)	(0.163)	(0.003)
Emotionally Unstable	0.003	–0.705***	0.009***
	(0.013)	(0.146)	(0.003)
Conscientious	0.024*	0.690***	–0.004
	(0.014)	(0.125)	(0.003)
Females			
Extroverted	0.050***	0.413**	–0.005*
	(0.014)	(0.156)	(0.003)
Agreeable	–0.001	0.226	0.001
	(0.014)	(0.156)	(0.002)
Open	0.039***	0.126	–0.001
	(0.015)	(0.138)	(0.003)
Emotionally Unstable	–0.033***	–0.786***	–0.001
	(0.012)	(0.161)	(0.002)
Conscientious	0.082***	1.186***	0.001
	(0.014)	(0.142)	(0.002)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Standard errors (in parenthesis) are clustered by state-month. Data is from the National Longitudinal Survey of Youth 1997 Cohort from the years 2000-2011, 2013 and 2015. Controls include the regional monthly unemployment rate in percentage points, gender, race, age and its square, level of education, marital status, number of children, urban residence dummy and ASVAB test scores. All estimations include month-year, region and occupation fixed effects.

We report our results from our main specification in Table 2.4.2. Column 1 shows no statistically significant relationship between economic fluctuations and income over personality traits. In column 3, those who are more extroverted see relatively smaller increases in unemployment insurance collection during economic downturns. On the other hand, those who are relatively more emotionally unstable experience worse labor market outcomes during economic downturns. In column 2, for every percentage point increase in the unemployment rate, someone with a standard deviation increase in emotional instability would see a 0.1 unit decrease in weeks employed and 0.2 percentage point increase in unemployment insurance take up relative to the baseline. There are no statistically significant effects of openness, agreeableness, or conscientiousness on labor market outcomes over the business cycle.

From Table 2.4.2 we conclude that individuals reporting higher levels of emotional instability have higher labor market penalties during recessions in comparison to those who are more emotionally stable. Additionally, those who are more extroverted see smaller increases in unemployment insurance take up than those less extroverted. To put these findings into perspective, we use the Great Recession as an example to identify the effects on labor market outcomes for emotional stability and extroversion traits. During the Great Recession, the national unemployment rate increased by about 5 percentage points. Using our coefficients from Table 2.4.2, an increase of this magnitude would decrease employment for the average worker by about 2.4 weeks. Additionally, workers would see a further 0.5 week decrease in their weeks of employment for every standard deviation increase in emotional instability. Unemployment insurance take up would also increase by 1.5 percentage points for the average worker, with an additional 0.2 percentage point increase for every standard deviation increase in emotional instability. On the other hand, unemployment insurance take up would decrease by 0.2 percentage points for every standard deviation increase in extroversion.

We can see this example play out in Figure 2.1. Prior to the 2008 recession, there was already a gap in weeks of employment between those whose self reported level of emotional instability were above and below the sample mean. Weeks of employment for those with more emotional stability were about three weeks greater than for those who were less emotionally stable. After the recession, this differential more than doubled as those who reported higher levels of emotional stability saw an average of nearly 42 weeks of employment while those less emotionally stable saw an average of 36 weeks. To this end, our results imply that workers with higher emotional instability experience increased volatility in employment over economic downturns, with recessions leading to larger employment losses for those with higher levels of emotional instability.

Table 2.4.2: Effects of the Business Cycle on Labor Outcomes Over the Big 5 Personality Traits

	Log of Income	Weeks Employed	Unemployment Insurance
Extroversion			
Extroverted	0.069***	0.571***	–0.003*
	(0.009)	(0.096)	(0.002)
Unemployment Rate (UR)	–0.005	–0.469***	0.015***
	(0.018)	(0.174)	(0.004)
Extroverted * UR	0.003	–0.020	–0.002*
	(0.004)	(0.062)	(0.001)
Agreeableness			
Agreeable	–0.028**	–0.055	0.001
	(0.011)	(0.110)	(0.002)
Unemployment Rate (UR)	–0.004	–0.488***	0.014***
	(0.018)	(0.179)	(0.005)
Agreeable * UR	–0.002	0.084	–0.000
	(0.005)	(0.059)	(0.001)
Openness			
Open	0.031**	0.118	–0.001
	(0.013)	(0.119)	(0.002)
Unemployment Rate (UR)	–0.005	–0.472***	0.015***
	(0.018)	(0.175)	(0.004)
Open * UR	–0.007	–0.093**	–0.000
	(0.006)	(0.042)	(0.001)
Emotional Instability			
Emotionally Unstable	–0.024**	–0.777***	0.002
	(0.010)	(0.113)	(0.002)
Unemployment Rate (UR)	–0.005	–0.451**	0.015***
	(0.018)	(0.175)	(0.004)
Emotionally Unstable * UR	–0.001	–0.094*	0.002*
	(0.005)	(0.047)	(0.001)
Conscientiousness			
Conscientious	0.056***	0.948***	–0.000
	(0.010)	(0.092)	(0.002)
Unemployment Rate (UR)	–0.005	–0.484***	0.015***
	(0.018)	(0.175)	(0.004)
Conscientious * UR	0.004	0.140***	–0.003***
	(0.005)	(0.037)	(0.001)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Standard errors (in parenthesis) are clustered by region-year. Coefficients of interest are reported for brevity. Data is from the National Longitudinal Survey of Youth 1997 Cohort from the years 2000-2011, 2013 and 2015. Controls include gender, race, age and its square, level of education, marital status, number of children, urban residence dummy, student enrollment status, and ASVAB test scores. All estimations include year, region, and occupation fixed effects. Each personality trait is regressed onto the dependent variables individually.

Figure 2.1: Differentials in Employment Volatility by Level of Emotional Stability

In Table 2.4.3 we estimate our baseline specification by gender. Interestingly, we find that males who are relatively more agreeable see an increase in unemployment insurance take up in comparison to those who are less agreeable. However, similar to Heineck and Anger [2010], we find there are no statistically significant effects associated with emotional instability for men. Instead, the effects of recessions on labor market outcomes over emotional instability are driven by females. Women who are a standard deviation more emotionally unstable experience an additional 0.2 week decrease in employment and 0.2 percentage point increase in unemployment insurance take up. This could be an indicator of discrimination, that women who are "emotionally unstable" are penalized more than "emotional" men.

Table 2.4.3: Effects of the Business Cycle on Labor Outcomes Over the Big 5 Personality Traits and Gender

	(1)	(2)	(3)
	Log of Income	Weeks Employed	Unemployment Insurance
Panel A: Males			
Extroverted * UR	0.003	–0.025	–0.001
	(0.006)	(0.075)	(0.001)
Agreeable * UR	0.001	0.096	0.002**
	(0.007)	(0.073)	(0.001)
Open * UR	–0.009	–0.203***	–0.001
	(0.006)	(0.052)	(0.001)
Emotionally Unstable * UR	–0.002	–0.025	0.002
	(0.006)	(0.069)	(0.002)
Conscientious * UR	–0.007	0.078	–0.005***
	(0.007)	(0.064)	(0.002)
Panel B: Females			
Extroverted * UR	–0.002	–0.066	–0.002
	(0.006)	(0.099)	(0.002)
Agreeable * UR	–0.005	0.084	–0.002
	(0.007)	(0.083)	(0.001)
Open * UR	–0.006	–0.004	–0.000
	(0.007)	(0.053)	(0.001)
Emotionally Unstable * UR	–0.006	–0.199***	0.001*
	(0.005)	(0.065)	(0.001)
Conscientious * UR	0.012*	0.151***	–0.001
	(0.006)	(0.055)	(0.001)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors (in parenthesis) are clustered by state-month. Data is from the National Longitudinal Survey of Youth 1997 Cohort from the years 2000-2011, 2013 and 2015. Controls include gender, race, age and its square, level of education, marital status, number of children, student enrollment status, urban residence dummy and ASVAB test scores. The unemployment rate is the regional monthly rate in percentage points. All estimations include month-year, region and occupation fixed effects. Each personality trait is regressed onto the dependent variables individually.

It may be the case that during recessions, when employers have more bargaining power, they choose to layoff individuals based on their own tastes and preferences. If for example certain personality traits tend to make workers less likable, employers may choose to lay off those who they favor the least. Thus it is possible that those who are more emotionally unstable see relatively worse labor market outcomes in recessions due to likability factors. On the other hand, it could also be the case that emotionally unstable workers are simply less productive during recessions, causing them to see fewer weeks of employment and increased unemployment insurance take up. If this is the case, self employed workers should see at least the same level of negative impacts on employment and unemployment insurance take up as their non self employed counterparts.

To parse out these effects, we estimate our baseline specification by self employment status. Those who are employees are subject to judgement on their work based on both employer tastes and their productivity. On the contrary, labor outcomes of self employed workers are determined by their own performance and not employer decisions. Consequently, we can assume that self employed workers outcomes are more likely due to their level of productivity. We report our findings based on self employment status in Table 2.4.4. We first find that statistically significant impacts on unemployment insurance take up for extroverted and emotionally unstable workers are concentrated amongst the non self employed workers. This finding is sensible since non self employed workers tend to have more unemployment benefits. Interestingly, effects of recessions on weeks of employment for emotional instability is predominantly driven by the self employed group. Specifically, workers with a standard deviation higher level of emotional instability have nearly 0.3 fewer weeks of employment with every percentage point increase in the unemployment rate. From this finding, it is reasonable to conclude that the effects on weeks of employment for the emotionally unstable is more likely a result of lacking productivity instead of employer tastes. Aside from emotional instability, self employed workers who are more agreeable see larger decreases in their income while those more open to new experiences see smaller decreases in income.

Table 2.4.4: Effects of Business Cycle on Labor Outcomes by Big 5 Personality Traits and Self-Employment Status

	(1)	(2)	(3)
	Log of Income	Weeks Employed	Unemployment Insurance
Panel A: Not Self Employed			
Extroverted * UR	0.004	–0.020	–0.002**
	(0.004)	(0.069)	(0.001)
Agreeable * UR	0.006	0.101	–0.000
	(0.005)	(0.067)	(0.001)
Open * UR	–0.005	–0.108***	–0.000
	(0.005)	(0.040)	(0.001)
Emotionally Unstable * UR	–0.000	–0.070	0.002**
	(0.005)	(0.052)	(0.001)
Conscientious * UR	0.001	0.120***	–0.004***
	(0.005)	(0.042)	(0.001)
Panel B: Self Employed			
Extroverted * UR	–0.016	–0.019	–0.002
	(0.024)	(0.105)	(0.002)
Agreeable * UR	–0.062**	0.048	–0.001
	(0.024)	(0.120)	(0.002)
Open * UR	–0.027	0.035	–0.002
	(0.032)	(0.127)	(0.002)
Emotionally Unstable * UR	0.011	–0.309***	–0.001
	(0.021)	(0.108)	(0.002)
Conscientious * UR	0.038	0.336**	0.003
	(0.031)	(0.146)	(0.003)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors (in parenthesis) are clustered by state-month. Data is from the National Longitudinal Survey of Youth 1997 Cohort from the years 2000-2011, 2013 and 2015. Controls include gender, race, age and its square, level of education, marital status, number of children, student enrollment status, urban residence dummy and ASVAB test scores. The unemployment rate is the regional monthly rate in percentage points. All estimations include month-year, region and occupation fixed effects. Each personality trait is regressed onto the dependent variables individually.

2.5 Robustness Checks

2.5.1 The Stability of the Big Five Personality Traits

Due to data limitations we are unable to observe personality traits over time, and rely on the assumption that personality is time invariant for our identification strategy. Cobb-Clark and Schurer [2012] looks at the stability of the Big Five over time and concludes that personality traits are stable over time for working-aged adults. They analyze the impact of adverse economic shocks on the Big Five personality traits. Specifically, they look at the effect of having at least five individual level adverse employment or income related events between 2006 and 2009 on personality changes. Overall, they find that their results are minimal. The largest effect of employment changes on personality occurs amongst men's emotional stability. The authors find that having at least five adverse employment and/or income related events decrease emotional stability for men by just 0.28 standard deviations. Using data from our sample, that translates to 0.37 units on a scale of 1 to 7. Other statistically significant effects on other personality traits amongst men and women are smaller and/or not statistically significant. They conclude that while personality traits are not literally fixed, they are stable. Therefore, we can uphold the assumption that labor market outcomes does not drive personality traits.

To verify that traits are stable in our sample, we look at data on traits that exist for two time periods. In the 2008 and 2010 survey waves, survey respondents answered questions that pertain to hard-working and rule-following traits. It is important to note that the trough of the Great Recession took place between the two survey waves. We first look at the mean difference in these traits between the two survey waves. We display our findings in the appendix in Table B1. Since personality traits are ranked on a scale of 1 through 7, the minimum and maximum of the difference between self-reported traits in 2008 and 2010 are -6 and 6 respectively. In Figure B2 we plot the mean difference in traits between the 2008 and 2010 survey waves. The majority of the sample has no change in self reported trait ranking. The largest mean difference occurs for support of rules and traditions with a mean of -0.14. In B2 we look at the kernel density of the mean difference across all traits listed in B1. The distribution shows the majority of the sample saw no changes in personality traits between 2008 and 2010.

2.6 Conclusion

While observable characteristics such as race, gender, education, etc. are strong predictors of earnings and other labor outcomes, there is still a large amount of variation between individuals who possess similar observable traits. Thus, a portion of the variation between individuals must be explained by unobservable characteristics (e.g., personality). Though there have been numerous studies in the psychology literature that look at the relationship between personality traits and various work outcomes, there are far fewer studies in economics that incorporate personality traits into their empirical models. Furthermore, because economists have used various measures of personality in their studies, not all results are comparable. Using data from the NLSY, our study sought to fill the gap in the literature to look at the impact of recessions on income, employment, and unemployment insurance take up over the Big Five personality traits.

For the total sample, we found workers who are more extroverted experience smaller levels of unemployment insurance take up compared to those who are less extroverted. Conversely, workers with higher self reported levels of emotional instability suffer greater employment losses and increased unemployment insurance take up during economic downturns compared to their more emotionally stable peers. Similar to findings from Heineck and Anger [2010], we find that the effects of economic downturns on labor market for the emotionally unstable are predominantly driven by females.

Furthermore, our results indicate that the widening gap in labor market outcomes by level of emotional instability is likely a result of a lack of productivity, since self employed workers who are less emotionally stable face greater employment losses than their more stable peers. Employers may benefit from understanding the needs of these workers better to help them reach their maximum productivity potential.

With the majority of significant results appearing for emotional instability, mental health status could also be at play here. Recall that emotional instability is also labeled as anxiousness, and could also include individuals suffering from depression or other disorders. With our results, this provides additional evidence that workers suffering from mental health conditions are less resilient in their labor market outcomes during economic downturns. To directly link mental health status and labor market outcomes during recessions, we would need an alternate data set, as the NLSY does not provide that information. We are exploring options of panel data surveys that include mental health status, personality traits, and labor market outcomes. Future research can also investigate causes of this lack of resilience, and interventions to address it.

Chapter 3

Ethnic networks and healthcare usage in India

Maya Ward

3.1 Introduction

Despite recent policy interventions to increase accessibility to healthcare, both maternal and infant mortality rates remain high in India. Home delivery remains relatively high, with the WHO estimating that 21% of births still taking place outside of institutional facilities (Pandey and Sengupta). This practice is generally not condoned by healthcare professionals, as it can lead to increased mortality rates for both mothers and infants since care is not readily available if complications arise. In 2017, India ranked in the top 20% in the world for neonatal death rates at 32 per 1000 live births, or nearly a quarter of the world's total neonatal births (Krishna et al. [2016]; for Child Mortality Estimation [2023]). Contributing to this statistic is that women in India tend to seek out care after complications arise, rather than preemptively (Fadel et al. [2015]). Consequently, India also has a relatively high maternal mortality rate (death of mother resulting from childbirth), at 143 per 100,000 in 2017 (Pandey and Sengupta). To put this in perspective, the United States has a maternal mortality rate of 19 per 100,000 and the UK just 5 per 100,000. In addition to childbirth, access to institutional healthcare more generally can contribute to increased use for pre- and post-natal visits, increasing the likelihood of survival for both mother and child. An increase in access theoretically translates to an increase in use, enabling earlier detection of communicable and non-communicable diseases, and better management of the conditions. However, as Kesterton et al. [2010] point out, access does not always positively correlate with usage. How then are we to increase trust and use among communities? To answer this question, I look to the influence of social networks on decision making.

Social networks have been shown to impact decision making (Sparrowe et al. [2001]) in fields from migration to employment to healthcare, and are studied across the globe (Neetha [2004]). The studies vary from contained experiments, where each individual's network is known, to larger scale studies using panel or cross-sectional data (Beaman and Magruder [2012], Bertrand et al. [2000]). Many of these studies investigate how information or some other type of intervention percolates through a given network, or work on the assumption that all members of a certain network share, to some extent, beliefs and news. This information could be for emergencies like hurricanes (Sadri et al. [2017]), healthcare decisions like vaccinations of children (2013), or general healthcare information (Griffiths et al. [2012]). Combining this background of networks with healthcare Deri [2005], uses the method from Bertrand et al. [2000] to examine if networks impact the decision of immigrants in Canada to seek healthcare from a general practitioner, dentist, or any type of consultation. They find positive evidence that networks do affect both the first stage demand for medical care and the decision to seek medical care, as well as the second stage in the demand for medical care (the decision to seek specialist care) being not significant as expected, since these decisions are largely made by the provider and not the individual themselves. Bertrand et al. [2000] work around the constraint of individual interviews, applying the concept of homophily group a large sample into distinct networks by their language and region of residence. Their paper investigates the relationship between immigrant networks and welfare use in the United States using a proxy variable for the network composed of a quality and quantity measure of said network. Most notably, Bertrand et al. [2000] and Deri [2005] use language-geography groups to specify ethnic networks, enabling the use of larger survey data sets and draw conclusions regarding a larger population. When stratified, I see that this clustering is also associated with socioeconomic status (SES).

Socioeconomic status has been linked to health both in India and abroad. In their 2015 paper, Childers and Chiou [2016] conclude that low SES individuals in India have higher rates of communicable diseases, while high SES individuals have higher rates of chronic disease such as cancer, diabetes, and heart disease. This follows from the concept of the SES health gradient (Lynch and Kaplan [2000]), which states that socioeconomic position are powerful determinants of exposure to damaging conditions for health and access to resources. Following the homophily principle of networks, people would naturally group themselves according to SES. Therefore, I must include it as a factor in the network specification. However, there is no single variable or indicator for SES. For health studies, there are a set of three main categories: wealth or income, education, and occupation (Duncan et al. [2002], Darin-Mattsson et al. [2017]). As India has a complex social class system determined by caste and religion, I use these instead of traditional measures for SES. Theoretically, only Hindu practitioners are members of a caste; there are a few from other religions folded in, most notably Muslim, as a result of conversion of Hindus to Islam and conquering groups integrated into the society starting in the 12th century (Ansari [1960]). However, as the vast majority are still Hindu, I create a "social group" variable as in Childers and Chiou [2016]. My data set does not offer as many caste subgroups, but I do split out OBC (other backwards castes), scheduled caste, and no caste for Hindus; and then the other major religions individually. The categories are constructed to be mutually exclusive.

This paper expands on the literature by exploiting the variation in language in a country to look at the network effects of its own population rather than just immigrants, and the first to do so by further using variation in religious and caste groups in conjunction with these language groups. Using this novel basis, I examine the effects of ethnic networks on maternal healthcare in India. While Bertrand et al. [2000] and Deri [2005] used only immigrant populations within a larger country, I am not limited to this to seek sufficient homogeneity in languages, since India has 22 official national languages, and over 100 spoken in the country. Using language or other groupings as a proxy for ethnic networks is helpful when trying to survey large groups of constituents for policy decisions, when individual surveys (Cai et al. [2015], Banerjee et al. [2013], Hoffmann [2017]) are not practical. I use a further layer to define the networks, comparing between groupings of geographic district and mother tongue additionally by social group, combining caste and religion.[1]

Using this unique comparison of network definitions, I look at healthcare outcomes for women related to maternal health. I investigate whether the delivery was at a health facility (also referred to as institutional delivery); whether the mother received a prenatal checkup, if it was performed in the first trimester, if it was at a health facility, and performed by a health professional; whether the mother received an antenatal checkup, and if that was performed within 2 days of birth. For all specifications, I see that the majority of the network variables are positive and significant, and interpret the result as evidence of networks. I take this as strong evidence of ethnic networks affecting utilization of healthcare services, with the variation between network specifications indicating which would be best to target for public health interventions.

3.2 Data and Empirical Strategy

3.2.1 Data Sources

I obtain data from the Demographic Health Survey (DHS) for India, Wave 7 (2015-2016). The DHS covers all of the measures of healthcare utilization, mother tongue of the respondent, and all other demographic variables. Previous studies have used census data; however, at this time, I am not able to find total population data in the census of India on language, language-caste, and language-religion by state, only language. Therefore, I adjust the sample totals by weights provided by the DHS to be able to accurately reflect the effect on the true population.

The DHS is a survey conducted in countries worldwide, with a standard questionnaire common to all countries, and additional local questions specific to each. The DHS in India uses the India National Family Health Survey (NFHS), conducted by the Ministry of Health and

[1]Previous studies using three layers include Mukong and Burns (2015) who create geographical by age-marital status cohorts when looking at maternal healthcare use in Tanzania, and Debnath and Jain (2018), who incorporate caste when examining healthcare claims and networks, using village (geographic area), caste group, and time of claim. While this third layer was tested for this paper, ultimately data size limitations led to using social group as an alternate in the second layer to compare definitions.

Family Welfare of the Government of India periodically, with the latest survey wave 4 covering 2015-2016. It is a survey of representative sample households in India and uses field offices in coordination with the International Institute of Population Sciences in Mumbai. The NFHS-4 fieldwork for India was conducted from 20 January 2015 to 4 December 2016 by 14 Field Agencies and gathered information from 601,509 households, 699,686 women, and 112,122 men. There are four questionnaires and data sets: household, men's, women's, and biomarkers. For this project, I will focus on the women's sample, as some of my outcomes of interest are around delivery and neonatal care.

3.2.2 Empirical Strategy

My empirical strategy is derived from Bertrand et al. [2000] and Deri [2005]. Like those authors, I employ a difference-in-difference estimation. The two sources of variation will be the quality and quantity measures of the network, mean healthcare usage and contact availability (CA). In words, the question would be as follows: given that your language or social group has a high mean usage of healthcare services, how does having high versus low contact availability affect your usage? I expect that for both high and low mean usage groups, an individual with high CA is more likely to use healthcare services than one with low CA. Furthermore, I expect that the effect of having a high CA will be higher for those from a language (or language-caste) group with a higher mean usage than the effect of having a high CA with a low mean usage for your language group. Indeed, these hypotheses follow the findings of previous literature (Bertrand et al. [2000], Deri [2005]).

The basic regression is as follows:

$$Y_{ijk} = \tau + \alpha Netw_{jk} + \theta CA_{jk} + X_{ijk}\beta + \gamma_j + \delta_k + \varepsilon_{ijk} \tag{3.1}$$

where Y_{ijk} is the healthcare service in question for language k over area j, CA_{ijk} is the contact availability measure, X is a set of controls, γ_j is the geographic fixed effect, δ_k is the language fixed effect, and ε_{ijk} represents the error.

The network variable is the cross of the quality and quantity measures:

$$Netw_{jk} = CA_{jk} \times MeanUsage_k \tag{3.2}$$

The quality measure, $MeanUsage_k$, is the mean healthcare use for the service Y, for the group k, over the entire population.

The quantity measure, contact availability or CA, is defined as follows:

$$CA_{jk} = \ln\left(\frac{C_{jk}/A_j}{L_k/T}\right) \tag{3.3}$$

Using the first definition as an example, C_{jk} is the total number of people in area j who are from language group k, with k as defined above, and A_j is the total number of people in area j. Thus, C_{jk}/A_j is the proportion of people in area j who are from language group k. The denominator represents the proportion of people in the whole country (T being total population[2]) who are from language group k. Following Betrand et al., I use the log of this ratio, which the authors showed to be robust.

When adding in social group to the network specification, the basic equation is the same, with only the definition of k changing: now, instead of representing the language group, it is the social group: the religion or caste of the individual.[3] Thus, the interpretation of the variables becomes: Y_{ijk} is the healthcare service in question for social group k over area j, CA_{ijk} is the contact availability measure for each individual's geographic-social group, X is a set of controls, γ_j remains the geographic fixed effect, δ_k becomes the social group fixed effect, and ε_{ijk} represents the error.

For the last definition, I have k remain as social group, and now change j to language group, with all other appropriate substitutions as above.

[2]The sample weights are applied directly to the total population calculation, and thus the network variable, rather than in the regressions.

[3]All of those listed under the "caste" are presumed part of the Hindu religion. This is as in Debnath and Jain (2018)

3.2.3 Issues for Identification

There are two major issues to identification: the reflection problem outlined by Manski [1993], and differential sorting. The reflection problem is that it may be impossible to disentangle the source of causation between the average group behavior and the behavior choice of an individual. Is the individual choosing to behave that way, and therefore is attracted to similar people, or does the average behavior of the group influence the individual to make that decision? In this situation, I assume that the individual does not choose to be part of a specific group, rather they are born into it. This is plausible for caste and tribe, but remains to be seen if it holds for religions, since people can change their religious affiliations from birth. Nevertheless, it is true for all individuals that they do not choose their mother tongue. One threat to this assumption is if an aspect of the network's culture drives the healthcare utilization, which while allowable, is not easily manipulated by policymakers. However, I assume that this culture aspect is taken care of by the various fixed effects that make up the ethnic group. In my definition, I am expanding ethnicity beyond simply language to include caste and religion, and therefore am attempting to capture these micro-cultures within larger ethnic groups.

Differential sorting refers specifically to differential geographic sorting. People who live in high-density areas of their language-caste group may be different in some unobservable way from those who live in low-density areas, but in a way that is correlated with their healthcare utilization decisions (Blavin [2011]). For example, suppose those who choose to live in low-density areas do so because their beliefs on healthcare do not align with that of the majority of their language-caste group. It could be that a particular group has strong beliefs on not using "modern" medicine, but instead using alternative practices. If a mother wishes to treat her child for certail illnesses in a hospital, she may move away from the high-density region to be able to do so without stigma. Blavin [2011] and Deri [2005] address this by constructing the network and CA variables at larger geographic levels (eg, state vs district), and then using those as instruments. Both authors also include a "years since migration" (YSM) control and interaction term with YSM and language group to control for the potential that immigrant location in low or high CA groups may change as the immigrants are in the country longer. While I do not have immigration data since I am looking at residents, it may be possible to do a proxy with years they have been in the household. I will do both techniques in a future iteration.

3.2.4 Summary Statistics

The summary statistics are included for reference when analyzing the results. To highlight, the representative agent has on average lower education (3 years), is about 30 years old, is most likely living in a rural area, and if they have kids, have two. They have between a primary and secondary education level. Note that only 28.3% of the sample is married, and 16.3% (who responded to the question) has ever had sexual intercourse. When reviewing the health services related to childbirth and care, it is important to keep in mind the results apply for this portion of the sample only. Since several variables applied to minute portions of the population, they were subsequently excluded from the covariate matrix. These were: sexual intercourse (and since only 26% of the total population answered), drinking, smoking, and living in a slum.

Table 3.2.2 shows the summary statistics for the health outcome variables. Note that all healths service variables are binary, with 1 indicating utilization and 0 no utilization. The majority of births (60 %) happen outside of an institutional facility (hospital or clinic) and residential home. This could include village doctors or other local and traditional institutions. Nearly one third of deliveries do occur in an institutional facility, with the remaining at the respondent's home. Of the 22% of respondents who received some form of prenatal or antenatal care, 27% of was from a skilled provider, and 16% received care in their first trimester. The average for receiving any form of prenatal care is not included as a regression outcome, but provided as a reference for the other outcomes regarding prenatal or antenatal care, as they are drawn from this portion of the sample.

For two typical measures of SES, wealth and education, Figures 3.1(b) and **??** confirm that caste and religion appear to be correlated with SES. The lower castes and minority religions tend to be lower than Hindus with no caste affiliation mentioned. Because these are the only groups in the data, it is not possible to parse out further associations with additional castes. This is contrary to what one may think, that SES and use of institutions for delivery are inversely correlated, motivating further investigation.

Table 3.2.1: Summary Statistics for Control Variables

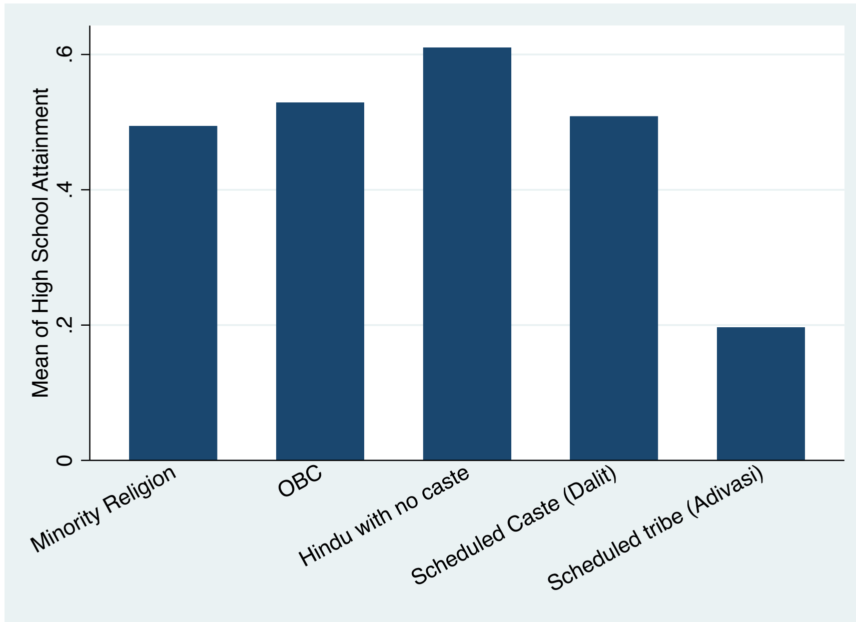
	Mean	SD
Respondent's current age	29.83	9.76
Wealth index within state	3.01	1.40
Ever had sexual intercourse	0.16	0.84
Lives in a Rural or Urban Area	0.71	0.45
Currently Smokes Tobacco Product	0.02	0.13
Able to read whole sentences	0.62	0.48
Drinks alcohol	0.02	0.16
Highest year of education	2.97	2.33
Highest educational level	1.43	1.02
Lives in a Slum Area	0.01	0.09
Marriage Status	0.80	0.49
Total children ever born	1.88	1.82
Observations	699686	

Note: Control variables used in later analyses. Wealth Index represents wealth quintiles, with 1 being the poorest and 5 the richest fifth of the population. Education level ranges from 0 to 3, with the categories (from least to greatest) being no education, primary schooling, secondary schooling, and higher education.

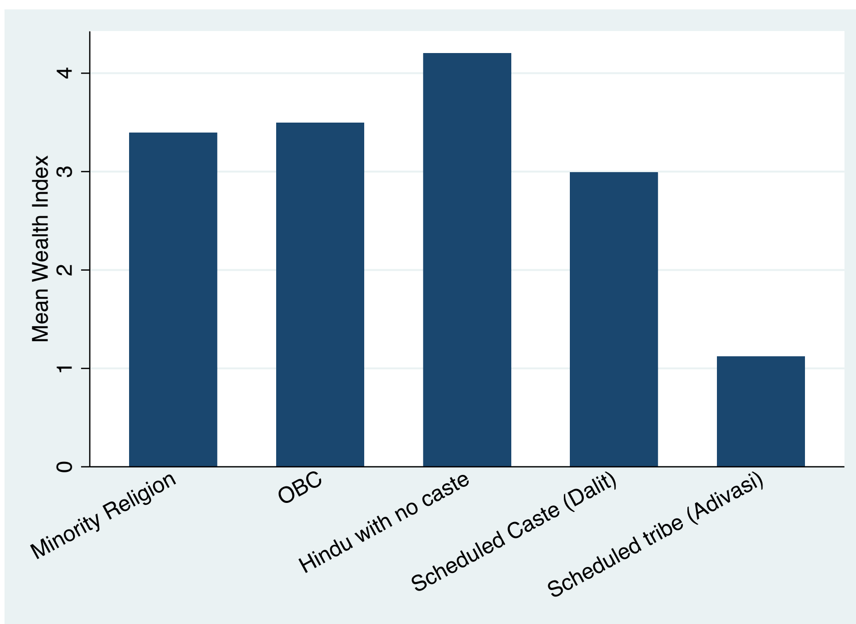
Table 3.2.2: Summary Statistics for Health Outcome Variables

	Mean	SD
Place of Delivery: Other	0.60	0.49
Place of Delivery: Public Facility	0.22	0.42
Place of Delivery: Private or NGO Facility	0.09	0.29
Place of Delivery: Residential Home	0.09	0.28
Institutional Delivery	0.31	0.46
Received Any Prenatal Care	0.22	0.42
Received prenatal care from skilled provider	0.27	0.44
Recevied antenatal visit during first trimester	0.16	0.36
Institutional Antenatal Care	0.18	0.39
Postnatal checkup performed by health professional	0.11	0.32
Received postnatal checkup within 2 days of birth	0.10	0.30
Observations	699686	

Note: All variables are binary indicators, so the means displayed represent the percentage of the population who used that maternal healthcare service. Institutional delivery or care includes services received at both private and public facilities. A "skilled provider" refers to either a doctor, nurse, midwife, auxiliary nurse midwives, or lady health visitors. This definition is taken from the DHS Final Report for 2015-2016.



(a) Attainment of High School Degree by Social Group



(b) Wealth Index by Social Group

Figure 3.1: Note: Attainment is a binary variable, with a value of one indicating attainment of a high school degree. Means displayed therefore represent the percentage of each group who have a high school degree. Social Groups are a compilation of religion and castes. Wealth Index splits the population into quintiles numbered 1 to 5, with 1 being the poorest and 5 being the richest. Results are weighted using population sample weights.

3.3 Results

I find varying degrees of evidence for networks based on the definition used, potentially indicating the variables that best capture the true social networks. For the original indicators of language and district, I see strong evidence of networks influencing maternal healthcare use across all outcome variables (Tables and 3.3.1). The coefficients are all positive and significant, with eight of ten significant at the one percent level. Positive significant coefficients indicate that the effect of living in a high CA area is larger for high usage groups than for low usage groups, and potentially mean reversion as in Deri (2005). With this information, policies should (counterintuitively) target high usage groups as they stand to gain more from small changes in their networks. It may be that high usage groups, while higher than their counterparts, are still low enough that they have much room for growth, and that interacting with peers stimulates this behavior to even higher degrees.

Tables and 3.3.2 show the regression results for the district-social group networks. All coefficients are positive, but only those for delivery in *other*, a private facility, or an institution are significant, along with prenatal care during the first trimester and in an institution. The district-social group specification seems to still capture the overall positive nature of the relationship between networks and maternal healthcare, but the indicator combination may not fit the true networks as well as the first definition.

The only significant coefficient for the language-social group regressions is for a prenatal checkup by a skilled professional (see Table 3.3.3), with two negative but insignificant coefficients for residential delivery (Table C3) and a postnatal checkup by a professional (Table 3.3.3). Non-significant coefficients indicate that there is no significant difference between living in a high CA area and belonging to a low or high usage group. Postnatal checkups by a professional are negative but insignificant for language-social groups: this implies that the effect of living in a high CA area is decreases healthcare use for high usage groups, but not by a significant amount.

Additional regressions breaking out the type of delivery for each network type can be found in the appendix (see Tables C1, C2, C3). The results match those of the corresponding neonatal regressions.

The results suggest that networks do indeed positively increase maternal healthcare use. However, given the changes in significance, the best proxy for networks is the combination of district and language. The decline in significance could be due to social group being an inferior substitute, or that district is simply a more accurate predictor of networks. It is logical that district would be a strong predictor of network. Consider an individual family – it is likely that a person would talk to a family member who lives down the street more often than one who lives across the country.

Table 3.3.1: Neonatal Health Regressions, using language-district groups

	(1) Institutional Delivery	(2) Prenatal Checkup By Professional	(3) Prenatal Checkup During 1st Trimester	(4) Institutional Prenatal Care	(5) Postnatal Checkup by Professional	(6) Postnatal Checkup Within 2 Days Of Birth
Network Effect	0.433***	0.273***	1.009***	0.375***	0.253**	0.278***
	(0.112)	(0.0879)	(0.197)	(0.0760)	(0.103)	(0.0803)
CA	0.132***	0.0745***	0.161***	0.0654***	0.0288**	0.0289***
	(0.0337)	(0.0234)	(0.0314)	(0.0132)	(0.0121)	(0.00832)
N	476615	476615	699680	699680	476615	476615
Mean of Y	0.311	0.271	0.157	0.184	0.112	0.102
SD of Y	0.463	0.445	0.364	0.388	0.315	0.303
District FE	✓	✓	✓	✓	✓	✓
Social Group FE						
Language FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parenthesis) are clustered by district, and results also have district and language fixed effects. Data is from the National Family Health Survey for India, wave IV (2015-2016), corresponding to wave VII of the Demographic Health Survey. Controls include age, age^2, wealth quintile, living in urban environment, literacy, education in years and level achieved, marital status, and number of children. Institutional delivery or care includes services received at both private and public facilities. A “skilled provider” refers to either a doctor, nurse, midwife, auxiliary nurse midwives, or lady health visitors. This definition is taken from the DHS Final Report for 2015-2016.

Table 3.3.2: Neonatal Health Regressions, using district-social groups

	(1) Institutional Delivery	(2) Prenatal Checkup By Professional	(3) Prenatal Checkup During 1st Trimester	(4) Institutional Prenatal Care	(5) Postnatal Checkup by Professional	(6) Postnatal Checkup Within 2 Days Of Birth
Network Effect	0.252**	0.0589	0.340**	0.175*	0.0689	0.114
	(0.123)	(0.0802)	(0.132)	(0.0904)	(0.104)	(0.0929)
CA	0.0757**	0.0143	0.0528**	0.0320**	0.00983	0.0142
	(0.0376)	(0.0210)	(0.0207)	(0.0158)	(0.0121)	(0.00977)
N	476619	476619	699686	699686	476619	476619
Mean of Y	0.311	0.271	0.157	0.184	0.112	0.102
SD of Y	0.463	0.445	0.364	0.388	0.315	0.303
District FE	✓	✓	✓	✓	✓	✓
Social Group FE	✓	✓	✓	✓	✓	✓
Language FE						
Controls	✓	✓	✓	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parenthesis) are clustered by district, and results also have district and language fixed effects. Data is from the National Family Health Survey for India, wave IV (2015-2016), corresponding to wave VII of the Demographic Health Survey. Controls include age, age^2, wealth quintile, living in urban environment, literacy, education in years and level achieved, marital status, and number of children. Institutional delivery or care includes services received at both private and public facilities. A "skilled provider" refers to either a doctor, nurse, midwife, auxiliary nurse midwives, or lady health visitors. This definition is taken from the DHS Final Report for 2015-2016.

Table 3.3.3: Neonatal Health Regressions, using language-social groups

	(1) Institutional Delivery	(2) Prenatal Checkup By Professional	(3) Prenatal Checkup During 1st Trimester	(4) Institutional Prenatal Care	(5) Postnatal Checkup by Professional	(6) Postnatal Checkup Within 2 Days Of Birth
Network Effect	0.745	0.525*	0.492	0.544	-0.00688	0.239
	(0.545)	(0.305)	(0.458)	(0.318)	(0.379)	(0.301)
CA	0.223	0.134	0.0736	0.0912	-0.00909	0.0188
	(0.171)	(0.0816)	(0.0730)	(0.0540)	(0.0500)	(0.0311)
N	476615	476615	699680	699680	476615	476615
Mean of Y	0.311	0.271	0.157	0.184	0.112	0.102
SD of Y	0.463	0.445	0.364	0.388	0.315	0.303
District FE						
Social Group FE	✓	✓	✓	✓	✓	✓
Language FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parenthesis) are clustered by district, and results also have district and language fixed effects. Data is from the National Family Health Survey for India, wave IV (2015-2016), corresponding to wave VII of the Demographic Health Survey. Controls include age, age^2, wealth quintile, living in urban environment, literacy, education in years and level achieved, marital status, and number of children. Institutional delivery or care includes services received at both private and public facilities. A "skilled provider" refers to either a doctor, nurse, midwife, auxiliary nurse midwives, or lady health visitors. This definition is taken from the DHS Final Report for 2015-2016.

3.4 Conclusion

Previous work on networks and healthcare focused on immigrant populations in developed Western countries, finding that these ethnic networks based on mother tongue do indeed influence health care decisions. This paper expands the definition of *ethnic* to include either caste or religion, in an attempt to better identify a cultural group, and focuses instead on the *resident* population of an Eastern developing country, India. I examine whether networks, acting through language-district, district-social, or language-social groups affect utilization behavior of women.

Two key findings emerge. First, I find that networks do affect maternal healthcare utilization behavior for women. The results show that a woman's behavior for visits to a delivery facility for childbirth and prenatal care in general are affected by the behavior of others in her cultural or ethnic network and are robust to both language-district and district-social network definitions. Furthermore, as the district-language definition had the most significant regression results, it appears to best capture the networks within the population. District seems a strong indicator of the "true" network, although it could be that the social group variable is not be well-defined enough in the data to get strong results. Second, this work presents evidence that some health care decisions are robust to the inclusion of caste and religion, adding to the literature on this topic. These findings emerge in spite of data lacking detailed groupings for caste, suggesting a more robust data set may yield stronger results.

These findings can help direct policies aimed at increasing healthcare use by signaling to policymakers if a specific group should be targeted to increase healthcare utilization, or if an at-large program would still be effective. If the decision of seeking out pre-natal care is significant when adding religion or caste, policymakers should look at the data by religious or caste group (after stratifying for language and state), and target information dissemination along these lines. In this way, the government (or other agency) can potentially save money since they will be addressing the problem at the source group, rather than wasting effort on all of those who are not in an at-risk group. This paper shows that for these targeted efforts, information is likely to spread within the network and reach the desired individuals.

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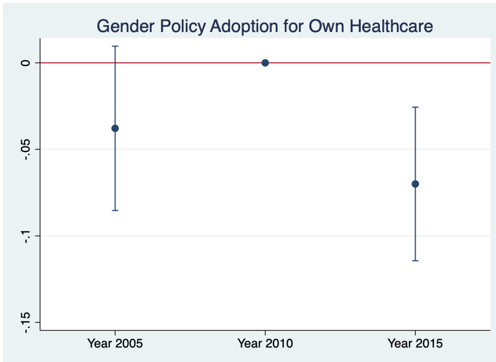
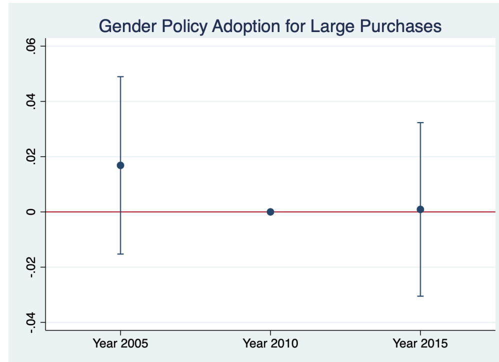
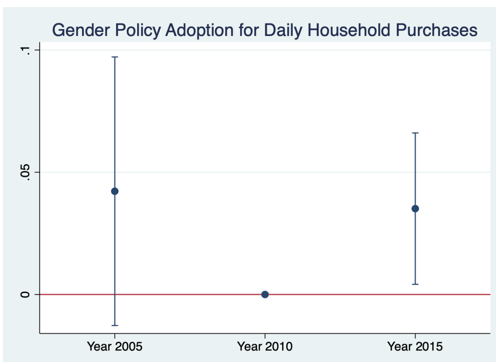
Appendix A



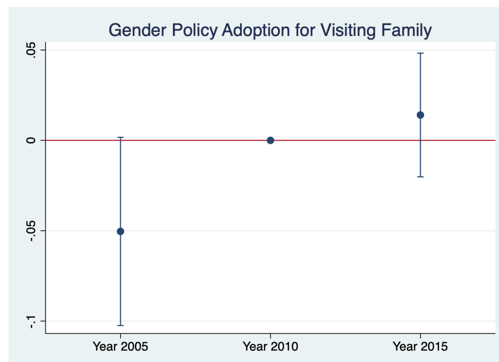
(a) Own Healthcare



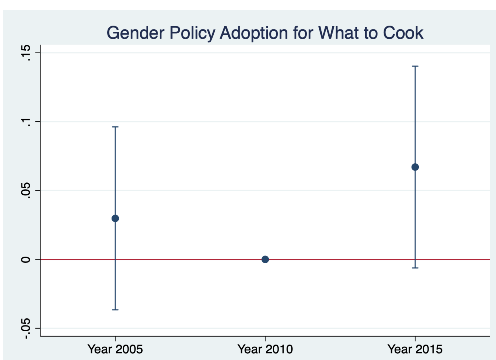
(b) Large Household Purchases



(c) Daily Household Purchases



(d) Visiting Family and Relatives



(e) What to Cook Daily

(f) Spending Own Wages

Figure A1: Note: Event studies for individual variables in bargaining index. Each represents Respondent having final say over the indicated topic. Coefficients from regression with fixed effects and controls, plotted. Year 2010 is baseline.

Appendix B

Table B1: Difference in Personality Traits Over Time

	Mean	Std. Dev.	Min	Max
Hard Working Traits				
Does More than Required	0.11	1.91	-6	6
Overall Hard Worker	0.07	1.74	-6	6
High Effort at Work	-0.09	1.35	-6	6
High Work Standards	-0.09	1.27	-6	6
Rule Following Traits				
Does Not Bend Rules	-0.07	2.10	-6	6
Did Not Break School Rules	-0.05	1.88	-6	6
Follows Rules	0.08	2.18	-6	6
Supports Rules and Traditions	-0.14	1.71	-6	6

Data is from the NLSY 1997 Cohort from survey years 2000-2011, 2013 and 2015. Personality traits are self-reported on a scale of 1 through 7 where 7 indicates the trait strongly applies to the individual. This table reports the mean difference between self reported personality traits in the 2008 and 2010 survey waves.

Table B2: Personality Trait Groupings

Response Choice	Inverted
Extroversion	
Extroverted, enthusiastic	No
Reserved, quiet	Yes
Agreeableness	
Critical, quarrelsome	Yes
Openness	
Open to new experiences, complex	No
Conventional, uncreative	Yes
Neuroticism	
Anxious, easily upset	No
Calm, emotionally stable	Yes
Conscientiousness	
Disorganized, careless	Yes
Hard Working Traits: 2008 and 2010 Average	
I have high standards and work towards them	No
I make every effort to do more than what is expected of me	No
I do not work as hard as the majority of people around me	Yes
I do what is required, but rarely anything more	Yes
Rule Following Traits: 2008 and 2010 Average	
I support long-established rules and traditions	No
Even if I knew how to get around the rules without breaking them, I would not do it	No
I do not intend to follow every little rule that others make up	Yes
When I was in school, I used to break rules quite regularly	Yes

Each response choice represents a question in the interview where respondents were asked to rate how much each statement applies to them on a scale of 1 to 7 where a higher rating indicates that the statement strongly applies. The scale for statements that relate to the opposite of each Big Five grouping is inverted so that a lower rating indicates the statement strongly applies to the individual. Ratings for questions applying to hard working and rule following characteristics are taken as the average of the response from the 2008 and 2010 survey waves.

Figure B1: Histograms of the Constructed Big Five Personality Traits

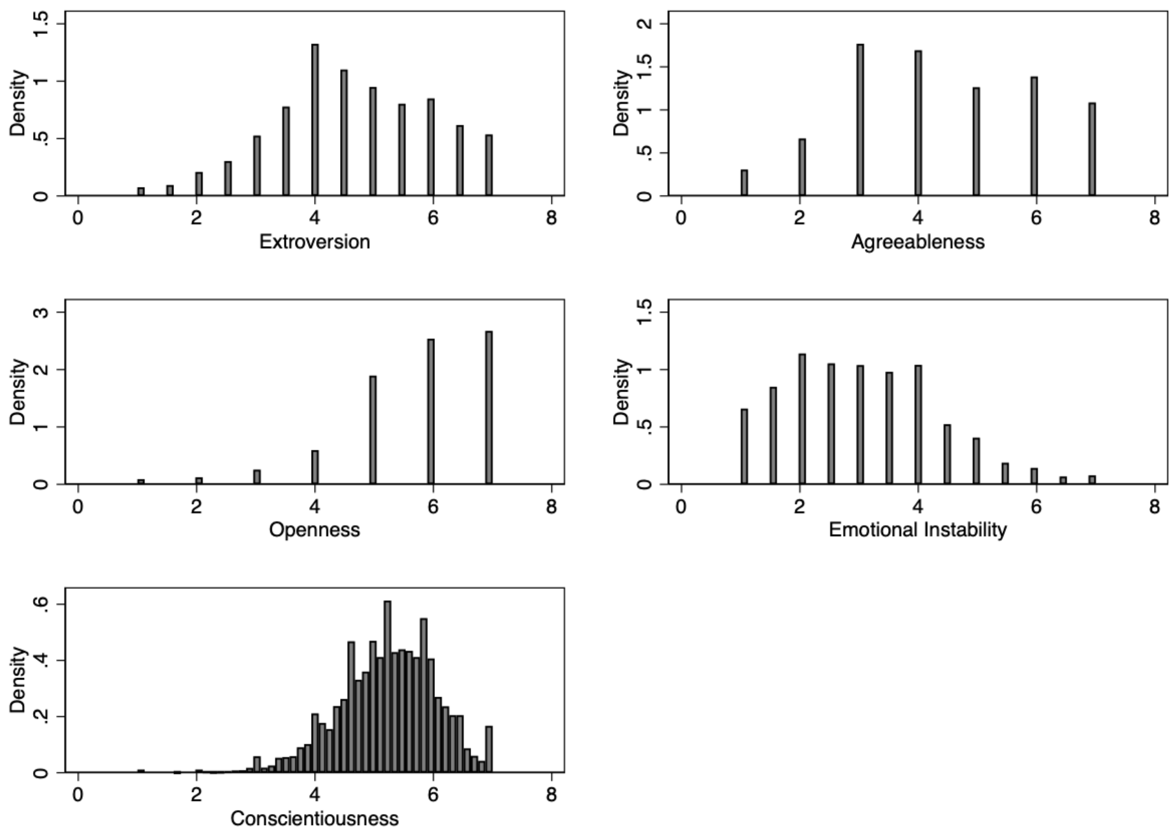
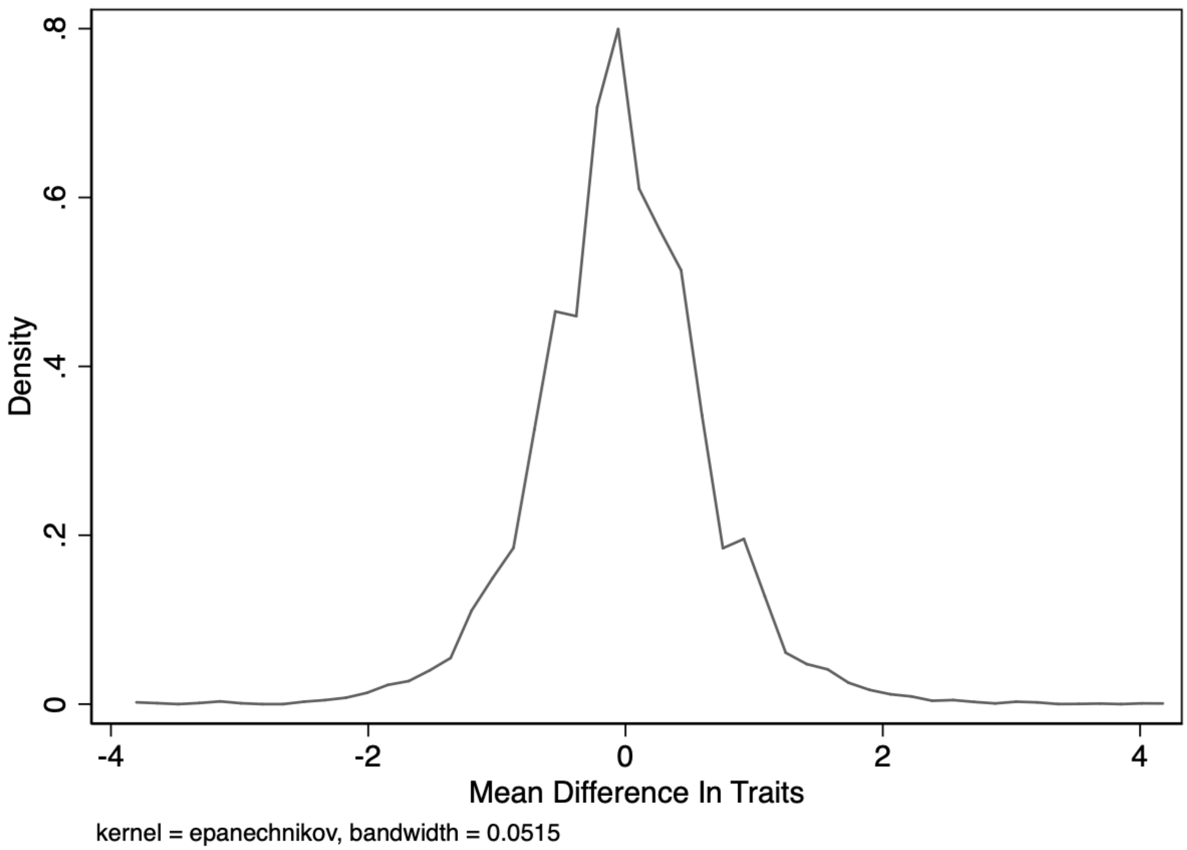


Figure B2: Kernel Density of Mean Differences in Traits Over Time



Appendix C

Table C1: Delivery Regressions, using language-district groups

	(1) Place of Delivery: Other	(2) Place of Delivery: Public	(3) Place of Delivery: Private or NGO	(4) Place of Delivery: Residential
Network Effect	0.165***	0.148***	0.0919***	0.0725*
	(0.0437)	(0.0527)	(0.0286)	(0.0392)
CA	0.102***	0.0323***	0.00680**	0.00504*
	(0.0276)	(0.0106)	(0.00275)	(0.00291)
N	476615	476615	476615	476615
Mean of Y	0.601	0.222	0.0893	0.0884
SD of Y	0.490	0.415	0.285	0.284
District FE	✓	✓	✓	✓
Social Group FE				
Language FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parenthesis) are clustered by district, and results also have district and language fixed effects. Data is from the National Family Health Survey for India, wave IV (2015-2016), corresponding to wave VII of the Demographic Health Survey. Controls include age, age^2, wealth quintile, living in urban environment, literacy, education in years and level achieved, marital status, and number of children

Table C2: Delivery Regressions, using district-social groups

	(1) Place of Delivery: Other	(2) Place of Delivery: Public	(3) Place of Delivery: Private or NGO	(4) Place of Delivery: Residential
Network Effect	0.105**	0.0456	0.134***	0.0722
	(0.0417)	(0.0438)	(0.0313)	(0.0451)
CA	0.0532**	0.0132	0.00823***	0.0181***
	(0.0259)	(0.00912)	(0.00301)	(0.00343)
N	476619	476619	476619	476619
Mean of Y	0.601	0.222	0.0893	0.0884
SD of Y	0.490	0.415	0.285	0.284
District FE	✓	✓	✓	✓
Social Group FE	✓	✓	✓	✓
Language FE				
Controls	✓	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parenthesis) are clustered by district, and results also have district and language fixed effects. Data is from the National Family Health Survey for India, wave IV (2015-2016), corresponding to wave VII of the Demographic Health Survey. Controls include age, age^2, wealth quintile, living in urban environment, literacy, education in years and level achieved, marital status, and number of children

Table C3: Delivery Regressions, using language-social groups

	(1) Place of Delivery: Other	(2) Place of Delivery: Public	(3) Place of Delivery: Private or NGO	(4) Place of Delivery: Residential
Network Effect	0.300	0.0934	0.146	-0.135
	(0.212)	(0.158)	(0.125)	(0.153)
CA	0.177	0.0121	0.0158	-0.00435
	(0.129)	(0.0314)	(0.0115)	(0.0137)
N	476615	476615	476615	476615
Mean of Y	0.601	0.222	0.0893	0.0884
SD of Y	0.490	0.415	0.285	0.284
District FE				
Social Group FE	✓	✓	✓	✓
Language FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parenthesis) are clustered by district, and results also have district and language fixed effects. Data is from the National Family Health Survey for India, wave IV (2015-2016), corresponding to wave VII of the Demographic Health Survey. Controls include age, age^2, wealth quintile, living in urban environment, literacy, education in years and level achieved, marital status, and number of children