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The Economics Department and Omicron Delta Epsilon congratulate **Milena Nikolova**, winner of the *2008 Dwight D. Eisenhower Society / R.M. Hoffman Family Memorial Prize in Economics*. The Eisenhower/Hoffman Prize is awarded to the economics student writing the best quantitative paper or project with public policy implications. Milena's paper, "The Effects of Intermarriage on the Earnings of Female Immigrants in the United States," is the lead article in this issue of the Gettysburg Economic Review.

The Economics Department and Omicron Delta Epsilon congratulate **Justin Holz**, winner of the *2008 Dr. and Mrs. William F. Railing Fund Fellowship for Faculty-Student Research in Economics*. The Railing Fellowship helps fund collaborative summer research between a student and an economics faculty member.

The Economics Department and Omicron Delta Epsilon congratulate **Chido Munangagwa**, recipient of a 2008 Mellon Grant.

The Economics Department and Omicron Delta Epsilon congratulate the following students for their achievements in the 2007-08 academic year:

Economics Graduation Banner Carrier
Milena Nikolova

2008 Outstanding Honors Thesis Award
Sam Marll & Milena Nikolova

2008 Economics Honors Graduates:
Marcelo Cardozo
Brad Garner
Megan Goodwin
Andrew Larsen
Sam Marll
Milena Nikolova
Tori Tran

Omicron Delta Epsilon would also like to thank our outgoing officers,
Glorianne Ponsart, Sam Marll, and Ashley Reynolds.

Contents

The Effects of Intermarriage on the Earnings of Female Immigrants in the United States

Milena Nikolova

ABSTRACT

This paper investigates the effects of intermarriage on the earnings of female immigrants in the United States. The main empirical question asked is whether immigrant females married to US-born spouses have higher earnings than those of immigrant females married to other immigrants. Using 1970 and 1870 samples of IPUMS data, I estimate an earnings equation through OLS. I also correct for the labor force selection bias using the Heckman procedure. I finally take into account the endogeneity of intermarriage and apply a two-stage least squares (2SLS) estimation procedure. I find that there is a positive marriage premium among immigrant females in the United States but a negative intermarriage premium for exogamously married females compared to endogamously married females. My results show that the longer the immigrant stays in the host country, the higher her wages, which is evidence for the assimilation effect over time. I find some evidence for a negative labor force selection bias among immigrant females. In other words, higher human capital women may select themselves out of the labor force, while lower human capital women are working for wages. Among those who are in the labor force, however, married females earn more than singles. I also conclude that being an immigrant from an English-speaking country does not have any impact on wages. Both premiums become statistically insignificant in difference from zero when 2SLS is used as an estimation procedure.

I. INTRODUCTION

This paper investigates the effects of intermarriage on the earnings of female immigrants in the United States. The main empirical question asked is whether there exists an intermarriage premium, i.e. whether immigrant females married to US-born spouses have higher earnings than immigrant females married to other immigrants. Studying the determinants of immigrants' earnings is important for several reasons. From an applied economics perspective, this study adds to the deeper understanding of labor market processes such as the transferability of human capital across countries. This research expands the existing literature by estimating both the marriage and intermarriage premiums for female foreigners. More precisely, I look at the wage differentials between intermarried and non-intermarried females. From the vantage point of sociology, intermarriage is important as it constitutes the highest degree of assimilation of immigrants (Wildsmith, Gutmann, and Gratton, 2003). From a public policy view, it is necessary to understand the implications of intermarriage on the economic assimilation of immigrants in order to make adequate public policy decisions. Lack of assimilation of immigrants may result in social and political turmoil. Understanding of the processes of immigration and assimilation is a necessary public policy prerequisite, especially given the relatively big flows of immigrants in the United States.

In this paper, by *intermarriage* or *exogamous marriage,* I mean the *de facto* marital union between a female immigrant and a US-born male. Any immigrant married to a non-native will be considered non-intermarried or *endogamously* married. [1]

This research question has its theoretical foundations in the marriage and assimilation literatures, and it belongs to the new branch of intermarriage literature. The marriage literature finds that married men have higher incomes than single men. Married men benefit from marriage as their spouses may choose to specialize in household production to support the human capital accumulation of their husbands, which would later lead to husbands' higher earnings (Becker 1973). At the same time, however, Becker (1985) argues that because raising children and housework require more effort than other household activities, married women are less productive in the labor market than married men for similar human capital endowments. Empirical results show that while the marriage premium is well established for males, there might be a zero or a negative premium for women. Neumark and Koremann (1992) find a positive female marriage premium but provide no compelling explanation for it.

Duleep and Sanders (1993) suggest that the gap between actual and potential earnings for the endogamously married females might not close over time, as they may take dead-end jobs to support their husbands' investment in human capital. In other words, upon arrival, immigrant wives may work more than their husbands to support them (Baker and Benjamin, 1997). Using Canadian data,

1 The terms "exogamous" and "endogamous" marriage are borrowed from Meng and Gregory's paper (2005).

Baker and Benjamin (1997) find empirical evidence for the family investment hypothesis for endogamously married females. Given the family investment hypothesis, decisions regarding the labor force for intermarried immigrants may differ from those of non-intermarried immigrant females. In particular, intermarried females might feel protected by their husband's social networks and financial support and might not feel the pressing need to perform to the best of their ability or take jobs with long hours, etc.

According to the assimilation literature, upon arrival, immigrants have lower earnings than natives because of the relative intransferability of skills across countries, insufficient host-country language skills, lack of information about the host country's culture and labor markets, as well as other factors. Chiswick (1978) proposes that this "initial earning deficiency" disappears as immigrants spend more time in the host country and gain country-specific knowledge and experience.[2]

The intermarriage literature is a new branch that unites the marriage and assimilation literatures. Using Australian census data for four years, Meng and Gregory (2005) were the first researchers to study intermarriage as a mechanism for economic assimilation. When they take into account the endogeneity of marriage, the intermarriage premium is 5% for men and 10% for women. Meng and Gregory's results cannot be extrapolated to the U.S. case since the immigrant pools are different in the two countries. While they account for the endogeneity of intermarriage, Meng and Gregory fail to correct for the labor force participation selection problem, which may be particularly severe in the female sample.[3]

Using French data, Meng and Meurs (2006) study the effects of intermarriage on the economic assimilation process for female and male immigrants. They propose that the intermarriage effects of economic assimilation should consist of an improvement in the language skills and the acquisition of information about the local labor markets. When individual characteristics and the endogeneity of intermarriage are taken into account, the premium rises to between 25% and 35%. The authors find that the magnitude of the intermarriage premium is higher for individuals with better language skills.

2 In addition, as time spent in the United States increases, immigrants are more likely to move to jobs where their productivity is higher, which is another explanation for the closing of the earnings gap (Chiswick, 1978).

3 With the labor force selection problem, we are concerned that the sample of working individuals is a non-random sample of the population since for those who are working, the reservation wage is below the market wage. In this sense, the selection bias is equally valid for male and for female samples. In addition, the selection bias could be present in the male sample as well since, just like females, males could be facing the same constraints and responsibilities within the household (i.e. time to take care of children, housework, etc). Given the traditional gender roles of females, however, it is generally agreed that the workforce selection bias is greater in female samples than in male samples (Korenmann and Neumark, 1992).

To date, Kantarevic (2004) is the only scholar to investigate the link between intermarriage and the economic assimilation of immigrants using United States IPUMS data for 1970 and 1980. He finds evidence for his selection hypothesis, which is based on the assumption that the relationship between intermarriage and assimilation is spurious, as the intermarried immigrants could well be a self-selected sample of all married immigrants. In other words, he considers a selection bias related to intermarriage rather than an endogeneity problem. Even if the place of birth does not affect productivity, the birthplace of the spouse may be related with work productivity. He further argues that this could be due to omitting a characteristic such as personal charisma or physical appearance. Kantarevic also examines the productivity hypothesis that native spouses facilitate human capital accumulation of their immigrant partners, implying that the earnings of intermarried immigrants must be statistically significantly different than those of identical non-intermarried immigrants.[4] Kantarevic finds a 2.5% premium for male intermarried immigrants, but the premium disappears once he corrects for the selection bias.

Given the literature, the question that this paper asks remains unanswered. Using IPUMS data for 1970 and 1980, and correcting for the labor force selection bias and the endogeneity of marriage, this project contributes to the intermarriage literature in at least two ways through *(i)* studying the female sample to provide a fuller view of the United States labor and marriage markets; *(ii)* studying both the intermarriage and marriage premiums among immigrants. In Section II, I present the model. In Section III, I discuss the data and methodology, followed by the empirical results in Section IV. Finally, Section V offers the concluding remarks.

II. EMPIRICAL MODEL

The formal theoretical model is developed by Kantarevic (2004), based on a standard immigrant earnings equation proposed by Borjas (1999). An immigrant has the following choices of marriage: to marry *endogamously* (i.e. marry another member of her own group or another foreign-born individual), to marry *exogamously* (i.e. marry a native-born individual), or to remain *single*. The individual's objective is to maximize her lifetime utility, which is a function of monetary and non-monetary gains associated with each type of marriage. The expected earnings and the marital state depend on the human capital and assimilation variables for each individual. The costs for each type of marriage depend on the individual characteristics and alternative determinants of costs.

4 Human capital accumulation stemming from intermarriage can be only imperfectly observed or not observed at all.

Based on Kantarevic's theoretical model, following empirical model can be developed:

$$Y_{it} = \alpha_0 + \alpha_1 Married_{it} + \alpha_2 Exogamous_{it} + \alpha_3 H_{it} + \alpha_4 A_{it} + \varepsilon_{it} \quad (1)$$

where the dependent variable Y_{it} is the log hourly wage, *Married* is a dummy variable having a value of one for married females and 0 for singles, *Exogamous* is a dummy variable having a value of one for exogamously married females and 0 for singles and endogamously married females, *H* is a vector of human capital and demographic variables (age, years of schooling, race, place of birth, place of residence, etc), and *A* captures the assimilation variable *years since migration*.[5] A detailed description of the dependent variables and the independent variables is available in Table 1 in the Appendix.

The regression equation for the Heckman labor force selection correction model is similar to the wage equation (1). It is observed only when the labor market wage is greater than the reservation wage for each female immigrant, i.e when the income earned is positive. The Selection mechanism is given by the following equations:[6]

Selection Mechanism:

$Zi^* = \gamma' Wi + \mu i$

$Zi = 1 \text{ if } Zi^* > 0,$

$Zi = 0 \text{ if } Zi^* \leq 0$

Prob (Zi = 1) = Φ (γ'Wi),

Prob (Zi = 0) = 1- Φ (γ'Wi).

Regression Model:

$Yi = \alpha + \beta i Xi + \varepsilon i$ observed if Zi = 1

$(\mu, \varepsilon i) \sim N[0,0,1,\sigma_\varepsilon, \rho]$

where Zi* is an indicator variable equal to 1 if the female earns income, and equal to 0 otherwise. *Wi* is a vector of human capital, demographic, and assimilation variables, as well as indicator variables for marital status.[7] The instrumental variables used in the selection equation are the number of own children under 5 years of age, and the number of own children aged 5-18.

If the decision to intermarry is independent of the potential earnings, we do not have an endogeneity problem and estimating Equation (1) with OLS would provide consistent and efficient estimates of the true population

5 The squared term of the variable years since migration was dropped from the model because it was highly col linear with the age and years since migration variable. An English language proficiency variable would have been a good additional assimilation variable. It is not included because of its unavailability for both sample years.

6 Greene (2007).

7 The maximum likelihood function for this model is given by Maddala (1983).

parameters. The decision to intermarry, however, may not be independent of the potential earnings, which makes the intermarriage variable endogenous. There may also be a simultaneity issue as intermarriage could be a factor causing and a result of economic assimilation. Since the nature of the marriage decision is endogenous, equation (1) is estimated through a two-stage least squares (2SLS) regression using the sex ratio and the probability of interethnic marriage as the two instrumental variables.

III. DATA AND METHODS

The ideal data for this paper would be panel data where the same individuals are traced over time. Due to the unavailability of such data, this paper, like the study by Kantarevic (2004), uses two cross-sectional samples (i.e. pooled data) - 1970 Form 1 State Sample and 1980 1% Metro Sample U.S. Census samples of Public Use Microdata Series (IPUMS-98).[8] These samples have information on age at first marriage and the year of immigration, which are used in the construction of a variable indicating whether an immigrant individual arrived as single.[9] Using at least two years of data allows to control for cohort and ageing effects (Kantarevic, 2004). [10]

The dependent variable in this study is the logarithm of hourly wage for females (in 2000 real dollars), constructed by dividing yearly wages by the product of average weeks of work and the average hours of work.[11],[12] The independent variables fall in two categories: human capital/demographic and assimilation variables (Table 1). The human capital/demographic variables are: age, $\frac{age^2}{1000}$, education, three indicator variables for place of residence (West, Midwest, South, where Northeast is the comparison group), six indicator variables for place of birth (North America, South America, Central America and the Caribbean, Asia, Africa, Other, where Europe is the comparison group), three indicator variables for race (Black, Asian, and Other Race, where White is the comparison group).[13]

8 The IPUMS-USA consists of thirty-eight samples drawn from every available census from 1850 to 2000. It is not panel data, i.e. it does not trace the same individuals over time. Both samples are 1-in-100 national random samples of the population. Sample availability, documentation and other information are available at www.ipums.org/usa/.

9 Later samples do not have the information about age at first marriage

10 An ageing effect occurs among all cohorts when a variable changes independently as cohorts grow older (Blanchard, Bunker, and Wachs, 2002). Cohort effects are independent of ageing effects and capture changes affecting populations born at a particular point in time (Blanchard, Bunker, and Wachs, 2002). As Kantarevic (2004) points out, the identification of each effect could be done with panel data or with at least several randomly selected cross-sections, which allows for cohorts to be tracked across years.

11 As the information about weeks and hours worked in 1970 are only available in intervals, these variables were recoded as having values equal to the average of each interval. For consistency, although direct, self-reported information is available for 1980, the interval variables were used in the same way as for 1970.

12 The appropriate CPI (All Urban Consumers) was used in the creation of the real values of all dollar variables.

13 The most populous category for each variable was used as an omitted (reference) category.

Age is used as a proxy variable for experience; given basic labor theory, I expect a positive coefficient estimate on age. In addition, the variable $\frac{age^2}{1000}$ accounts for the possible concavity of earnings as a function of age.[14] I expect a negative coefficient estimate on the squared term of age. Since education increases marginal productivity and therefore wages, I expect a positive coefficient estimate on years of schooling. The assimilation variable, years since migration, is a count variable and I expect a positive coefficient estimate on it. [15]

The female sample is limited to foreign-born female singles and spouses, aged 16 to 65. Using the variables for the length of marriage and year of immigration, the sample is restricted to females who came to the United States as unmarried.[16],[17] The female sample consists only of females whose native language is not English. The rationale is that English-speaking immigrants could assimilate at a faster rate than non-English speaking immigrants, thus pulling up the average earnings of female immigrants.[18] The male sample is limited to individuals aged 14 to 70 to allow an age difference between actual and potential spouses at both ends of the age distribution.

Next, the dummies endogamous, exogamous, and single are created. The exogamous indicator variable has a value of one for all foreign-born females who are married to the US-born male heads of households and whose husband's birthplace is the United States. It has a zero value for singles and for endogamously married females. The endogamous indicator variable has a value of one for all foreign-born females aged 16-65, married to foreign-born male heads of households.[19], [20]

To correct for selection bias related to the labor force participation, two instrumental variables are used in the Heckman procedure: number of own children under age of five and number of own children aged 5 to 18. I expect that having own children lowers the probability of being in the labor force. The

14 The division by 1000 is done to avoid scaling effects.

15 The square term of the variable was considered as an additional covariate to capture any concavity of the earnings function over time but was not included in the main regressions due to collinearity issues.

16 In this paper, the category "separated" is treated as "married."

17 Technically, even females who were married upon arrival have the chance to intermarry through divorcing their spouses. Those who face the *actual* decision of intermarriage, however, are the non-married individuals (i.e. divorced, widowed, and never married individuals) (Gregory and Meng, 2005).

18 This restriction was later relaxed and for comparison purposes, results from the full sample are provided in Table 9 in the appendix. It is important to point out that the full sample regression results are not substantially different from the main regression results.

19 The married sample of females in this paper is therefore limited to immigrant spouses married to heads. This is a relatively good way to look at the data since 95% of the married men were heads of household and 5.5% of the married women were heads of household. In other words, 94.5% of the married women were spouses.

20 A different specification check could be including a dummy variable for endogamously married females whose spouses are non-US-born native English speakers. Table 10 provides the results from this model.

probability of interethnic marriage and the sex ratio are used as instruments in the 2SLS model to correct for the endogeneity of intermarriage. First, the probability of interethnic intermarriage for females, is:

$$Z_{isg} = (m_{sg}/M_g)/(n_s/N)$$

where m_{sg} is the number of single (never married, divorced, and widowed) men in state s of country of origin g (Kantarevic, 2004). M_g is the total number of unmarried men in country of origin g in all states; n_s is the number of unmarried US-born males in a state s, and N is the total number of unmarried men in all states. [21] The smaller the value of the probability of marrying within is, the higher the likelihood of marrying a native spouse is.

The likelihood of intermarriage also depends on the sex ratio is defined as:

$$SEXRATIO_f = M_{msg} / M_{fsg}$$

where M_{msg} and M_{fsg} are the numbers of males and females, respectively, in the specific nativity-state group. The higher the sex ratio, the more likely it is for the female to marry within her own native group.[22]

All four instrumental variables (number of children under age of 5, number of children aged 5 to 18, sex ratio, probability of marrying within) theoretically satisfy the exclusion restriction. The number of children in the respective ages affects the decision to enter the labor force but does not directly affect wages. Similarly, the probability of interethnic marriage and the sex ratio affect the marriage decision but not wages.[23]

This paper uses three different estimation techniques: ordinary least squares regression with robust standard errors (OLS), Heckman labor force selection correction, and two-stage least squares (2SLS).[24],[25] I expect the OLS estimates to be biased and inconsistent due to the selection and endogeneity problems.[26]

21 The terms single (never married, divorced, and widowed) and unmarried are used interchangeably in this paper.

22 The instrument for the probability of marrying within could be thought of as measuring the relative availability of foreign-born potential spouses over native potential spouses, while the sex ratio captures the relative avail ability of foreign men to foreign women, i.e. the intra-nativity group competition for spouses.

23 The appropriate census weights were used in the creation of the sex ratio and the probability of marrying within.

24 The reference group in all models is singles.

25 Equation (1) is first estimated through OLS with robust standard errors to correct possible heteroskedasticity, which is common in cross-sectional data. I also added the sample weights to make the regression representative of the population data.

26 To address the selection problem regarding the labor force participation, the Heckman correction procedure is followed with the number of own children in the respective age groups as instruments. To address the problem that the choice of intermarriage is endogenous, the two-stage least squares procedure is performed using the sex ratio and the probability of marrying within as instruments.

IV. RESULTS

1. Summary Statistics

The final sample consists of 28,970 female immigrants, 11,313 in 1970, and 17,657 in 1980. The intermarried females were 6,386 or around 50% of all *married* females during both sample years. In 1970, the number of exogamously married female foreigners was 3,299, or 55% of all married foreigners, and in 1980, the total was 3,087 or 45% of all married female foreigners. Table 2a shows the places of origin for the most populous groups of female immigrants as well as the percentage of exogamously and endogamously married, and single females. Among the countries of origin with the highest share of exogamously married females are Sweden (36% of all immigrants in the sample were exogamously married), Germany (34% of all immigrants were intermarried), and Italy (29% of all immigrants in the sample were exogamously married). The countries with the lowest share of exogamously married females are India (12%), China (14%), and Turkey (15%). The countries with the highest percentage of endogamously married females are Yugoslavia (33%), Italy (31%), China (31%), and the USSR (31%). Table 2b shows the intermarriage rates among individuals from the same place of origin, measured by the proportion of exogamously married people of all married individuals from the same country of origin. The countries with the highest percentage of intermarried immigrants are Japan (73%), Germany (71%), and the African countries (66%).

Table 2a: Major Places of Origin and Marriage Rates

	Total	Exog	Std.dev	Endog	Std. Dev	Single	Std. dev
Mexico	4,641	0.20	0.40	0.28	0.45	0.52	0.50
Central America	960	0.17	0.38	0.21	0.41	0.61	0.49
Cuba	1,872	0.08	0.28	0.22	0.42	0.69	0.46
South America	1,381	0.16	0.37	0.17	0.38	0.66	0.47
Sweden	216	0.36	0.48	0.19	0.39	0.45	0.50
Italy	2,412	0.29	0.45	0.31	0.46	0.41	0.49
Germany	3,443	0.34	0.48	0.14	0.35	0.51	0.50
Yugoslavia	369	0.20	0.40	0.33	0.47	0.48	0.50
USSR	847	0.22	0.42	0.31	0.46	0.47	0.50
China	773	0.14	0.34	0.31	0.46	0.55	0.50
Japan	498	0.24	0.43	0.09	0.29	0.67	0.47
India	170	0.12	0.33	0.26	0.44	0.62	0.49
Turkey	101	0.15	0.36	0.22	0.41	0.63	0.48
Africa	266	0.26	0.44	0.14	0.34	0.60	0.49
Number of Observations		**6,386**		**6,549**		**16,035**	

(1) The data on percentage intermarried reports the fraction of all individiuals of a particular place of origin who are married to a US-born husband. Similar calculations were performed for the endogamous and single groups for both sample years

(2) The data are listed only for selected major places of origin

Table 2b: Intermarriage rates among major groups

	Number Intermar	Mean	Std. Dev
Mexico	2,210	0.41	0.49
Central America	372	0.45	0.50
Cuba	575	0.27	0.45
South America	468	0.49	0.50
Sweden	118	0.66	0.48
Italy	1,434	0.48	0.50
Germany	1,678	0.71	0.46
Yugoslavia	193	0.38	0.49
USSR	452	0.42	0.49
China	348	0.30	0.46
Japan	165	0.73	0.45
India	65	0.32	0.47
Turkey	37	0.41	0.50
Africa	106	0.66	0.48

(1) The data on percentage intermarried reports the fraction of all married individiuals of a particular place of origin who are married to a US-born husband for both census years

(2) The data are listed only for selected major places of origin

Table 3 shows the sample summary statistics for the intermarried and non-intermarried female immigrants. First, the age structure seems to be similar for all three groups, where all groups have a younger average age in the 1980 sample than in the 1970 sample. The exogamous group has spent more years in the US on average than the endogamous group and the difference between the groups is larger in 1980 than in 1970. The single group has spent the shortest amount of time in the US among the three groups. On average, the exogamous group has more years of education than both the single and the endogamous group for both time periods and the single group has more years of schooling than the endogamous group for both census years. The level of educational attainment was higher in 1980 than in 1970 for all groups. The summary statistics on husband's years of schooling and real annual wages (in 2000 constant dollars), and total family annual income (in 2000 constant dollars) are important for putting the analysis in a family context. [27]

27 Exogamously married females and their husbands on average have more years of schooling than endogamously married females and their husbands. This is one example of assortative marriage, i.e. higher human capital men marrying higher human capital women. This statistic could have potential effects on the work outcomes for women. In particular, relying on the higher incomes and social networks of their husbands, exogamously married females could choose to work less or choose not to take jobs that require a lot of effort.

Table 3: Sample Summary Statistics: Intermarried and Non-Intermarried Females

	1970					
	Exogamous		Endogamous		Single	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev
Age	42.27	13.91	44.90	14.90	41.81	17.79
Years In US	30.33	16.38	29.02	17.79	23.43	17.02
Years of Schooling	13.91	3.44	12.21	4.21	12.73	4.18
Husband's years of schooling	14.36	0.71	12.93	1.70		
Husband's real annual wage income	36,382	3,888	31,364	8,584		
Total real family annual income	46,847	6,404	42,841	6,510	49,437	6,542
Number of observations	**3,299**		**2,701**		**5,313**	
	1980					
	Exogamous		Endogamous		Single	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev
Age	34.26	9.61	33.75	9.89	35.76	15.37
Years In US	19.61	7.61	15.34	8.03	14.74	8.23
Years of Schooling	15.21	3.52	13.88	4.21	14.05	4.09
Husband's years of schooling	15.21	0.78	13.60	2.23		
Husband's real annual wage income	32,637	3,089	27,254	6,143		
Total real family annual income	49,461	6,432	42,554	7,393	42,113	7,179
Number of observations	**3,087**		**3,848**		**10,721**	

On average, the husbands of the exogamously married females have more years of schooling than their spouses in both years, and the exogamously married females have more years of schooling than the husbands of the endogamously married females in 1970. The group with the lowest average level of education is the endogamously married females in 1970 and their husbands in 1980. The husbands of the exogamous group had higher average real annual wages than the husbands of the endogamous group for both years. The average real annual wages for both groups of husbands were lower in 1980 than in 1970. Similarly, the average total real family annual income for the exogamously married females was higher than that of their endogamously married counterparts for both years. The singles had the highest total average income in 1970 and the lowest average income in 1980.

Table 4 shows the average real hourly wage (in 2000 constant dollars) for the exogamous and endogamous groups.

Table 4: Average Wages, Weeks and Hours Worked

	Exogamous			
	1970		1980	
	Mean	Std. dev	Mean	Std. Dev
Hourly Wage	15.91	25.65	12.22	12.24
Weeks Worked	42.66	13.04	43.15	12.99
Hours Worked	35.05	10.46	36.48	9.51
Observations	1,777		1,907	

	Endogamous			
	1970		1980	
	Mean	Std. dev	Mean	Std. Dev
Hourly Wage	14.76	14.29	12.52	11.63
Weeks Worked	42.99	12.59	42.99	12.98
Hours Worked	35.45	10.36	37.14	8.54
Observations	971		1,759	

	Single			
	1970		1980	
	Mean	Std. dev	Mean	Std. Dev
Hourly Wage	13.79	14.10	11.75	11.67
Weeks Worked	43.53	12.59	44.21	12.26
Hours Worked	36.72	9.87	37.70	9.28
Observations	3,758		6,961	

1) The hourly wage is reported in 2000 constant US dollars.

2) The interval data were used for the hours and weeks worked as well as for the construction of the hourly wage variable

In 1970, the average hourly wage was $15.91 for intermarried females, $14.76 for non-intermarried females, and $13.79 for singles. In 1980, the average hourly wage was lower for all groups, with the highest wage of $12.52 for the endogamous group, which is similar to Kantarevic's findings for the male sample. This could be reflective of the recessions during the 1970s or could be a result of the quality of the immigrant pool in 1980. Table 4 also shows the hours per week and weeks worked. In both years, singles had the longest hours of work and weeks worked. In 1970, the endogamous group had more average weeks worked and hours per week worked than the exogamous group. In 1980, the exogamous group worked on average more weeks than the endogamous group but the endogamous group worked on average longer hours per week.

2. OLS Regression Results

Table 5 presents the results from the earnings equation (1) estimated through OLS with robust standard errors, the Heckman procedure, and the 2SLS. Let us consider the OLS regression results, which I suspect are likely to be biased and inconsistent given the selection bias and the endogeneity problem.

The coefficient estimate on the marriage dummy is positive and statistically significant in difference from zero. In particular, on average, the predicted value of the earnings of married female immigrants is approximately 6.2% higher than those of their single counterparts. This result is contrary to Becker's (1985) theoretical framework. It is important to point out that the females in this particular sample are only immigrant females, who could have different family experiences and work patterns than the average American-born woman. The coefficient estimate on the exogamous indicator variable from the OLS regression is negative and statistically significant in difference from zero. It indicates that the predicted value of the earnings for exogamously married females is around 6.1% *lower* than that for the endogamously married. The coefficient estimates on age and its squared term, which are statistically significant in difference from zero, show that earnings are an increasing and concave function of age. An additional year is expected to increase the predicted value of the real hourly earnings of female immigrants by around 4.2%, holding constant the influence of the other included independent variables.

An additional year of schooling is expected to increase the predicted value of real hourly wages by around 4.5%, holding constant the influence of the other included independent variables.

Table 5: Estimates of the Earnings Equation			
	OLS robust	*Heckman*	*2SLS*
Core Regressors	Coeff. Estimate	Coeff. Est	Coeff. Est.
Married	**0.062*****	**0.069*****	**-1.054**
	(0.014)	**(0.017)**	**(1.535)**
Exogamous	**-0.061*****	**-0.061*****	**-0.209**
	(0.018)	**(0.018)**	**(0.693)**
Age	4.248e-02***	4.076e-02***	1.074e-01
	(2.910e-03)	(3.597e-03)	(1.018e-01)
Age Squared	-0.470***	-0.449***	-1.410
	(0.037)	(0.045)	(1.479)
Education	0.045***	0.044***	0.044***
	(0.002)	(0.002)	(0.004)
Born N. America	-0.227**	-0.228**	-0.164
	(0.094)	(0.094)	(0.174)
Born S. America	0.006	0.007	-0.055
	(0.026)	(0.026)	(0.084)
Born C. America -Caribbean	-0.032**	-0.032**	-0.043
	(0.016)	(0.016)	(0.050)
Born Asia	0.041	0.043	0.015
	(0.030)	(0.030)	(0.051)
Born Africa	0.122	0.125*	0.070
	(0.075)	(0.075)	(0.115)
Born Other	-0.056**	-0.053**	-0.113
	(0.026)	(0.026)	(0.102)
Midwest	-0.035**	-0.035**	-0.005
	(0.017)	(0.017)	(0.063)
South	-0.144***	-0.143***	-0.153***
	(0.017)	(0.017)	(0.029)
West	-0.060***	-0.060***	-0.073***
	(0.015)	(0.015)	(0.023)
Black	0.060***	0.060***	-0.055
	(0.023)	(0.023)	(0.172)
Asian	0.049	0.047	0.102
	(0.031)	(0.031)	(0.063)
Other race	-0.005	-0.005	-0.019
	(0.045)	(0.045)	(0.056)
Years in the Untied States	**0.002*****	**0.002*****	**0.017**
	(0.001)	**(0.001)**	**(0.026)**
Indicator Year 1980	-0.195***	-0.196***	-0.244***
	(0.013)	(0.013)	(0.085)
Constant	0.938***	0.994***	0.204
	(0.058)	(0.090)	(1.204)
rho		-0.038	
		0.047	
sigma		0.631	
		0.006	
lambda		**-0.024**	
		0.030	
Observations	13,417		13,417
R-squared	0.13		

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The coefficient estimates on years of schooling is statistically significant in difference from zero. Relative to the wages of immigrants born in Europe, the predicted value of the earnings of the immigrants born in North America are likely to be 22 % lower, holding constant the influence of the other included independent variables. The coefficient estimates on the indicator for North American origin is statistically significant in difference from zero.[28] Relative to earnings of European immigrants, the predicted value of the earnings of immigrants born in South America, Asia, and Africa are higher, but the coefficient estimates are not statistically significant in difference from zero. Relative to the wages of immigrants born in Europe, the predicted earnings of the immigrants born in Central America and the Caribbean are lower by about 3.2%, holding constant the influence of the other included independent variables. Relative to the earnings of immigrants born in Europe, the immigrants born in other regions are likely to be approximately 5.6% lower, holding constant the influence of the other included independent variables. Relative to the earnings of immigrants living in the North East, immigrants living in the Midwest, South, and West regions are lower. Relative to the earnings of White immigrant females, the earnings of Black immigrants are around 6% higher, holding constant the influence of the other included independent variables.

The coefficient estimates on Asian and other race are positive but not statistically significant in difference from zero. The coefficient estimate on years spent in the United States is positive and statistically significant in difference from zero. In particular, each additional year spent in the United States increases the predicted value of the real hourly wage by about 0.2%, holding constant the influence of the other included independent variables. This result suggests that an assimilation process is taking place, i.e. immigrant wages are increasing as the number of years they spend in the host country increase. Last, the coefficient estimate on the indicator variable for 1980 suggests that the predicted value of the real hourly earnings in 1980 were 19.5% lower than those in 1970, holding constant the influence of the other included independent variables. This result could be an echo effect from the economic recessions in 1973 and 1979.[29]

28 The only North American country is Mexico, since immigrants from Canada are English-speaking and are not included in the sample. The coefficient estimate on being born in North America changes its sign when the full sample results are introduced in Table 9 but the coefficient estimate is not statistically significant in difference from zero.

29 In general, the total private seasonally adjusted average real wages in 1980 were 5. 46% lower than the cor responding value for 1970 for the US economy. Source: author's calculations using BLS data. http://data.bls.gov.

3. Heckman Selection Correction Regression Results

Table 5 contains the earnings regression results, while Table 6 in the Appendix contains the Probit results. In this section, I discuss only selected results pertaining to the probability of being in the labor force and the corrected earnings results. First, the Probit results indicate that most coefficient estimates have the expected signs and are statistically significant in difference from zero. As expected, being married, as well as the presence of own children, have a negative impact on the probability of being in the labor force. The coefficient estimate on the exogamous dummy indicates that relative to the endogamously married and singles, exogamously married immigrants have a lower probability of being in the labor force. Older age and having more years of schooling increase the probability of working for wages. Relative to immigrants born in Europe, immigrants born in all other places but North America and Central America and the Caribbean, have lower probability of working for wages. The coefficient estimate on the indicator for birthplace in North America and Central America-Caribbean are both statistically insignificant in difference from zero. Relative to immigrants living in the Northeast, immigrants living in all other regions but the Midwest have a lower probability of being in the labor force. The coefficient estimates on all three indicator variables for place of residence are not statistically significant in difference from zero. All other races have higher probability of working for wages relative to Whites, which is the comparison group. Interestingly, the longer the immigrants stay in the United States, the lower their probability of being in the labor force. As mentioned above, these females could be supported by their husband's income and status in society. Last, immigrants observed in 1980 had a higher probability of being in the labor force relatively to those observed in 1970.

The Heckman results indicate that the marriage premium is around 7% and statistically significant in difference from zero. The intermarriage penalty is around 6.1% and is statistically significant in difference from zero.[30] The coefficient estimates on all other included variables have not changed much from the OLS results. The coefficient estimate on lambda is negative, but not statistically significant in difference from zero, indicating that there is a weak support for the negative selection bias in the labor force among female immigrants. In other words, my results show weak evidence that higher human capital immigrants are not working for wages. At the same time, among those

30 Kantarevic's Heckman results for the male sample indicate a positive but insignificant premium. Correcting for an intermarriage selection bias, rather than the endogeneity of intermarriage, Kantarevic calculates the assimilation effect, i.e. the difference between the coefficient estimates on age (age squared), years since migration (years since migration squared) over the two time periods.

who are working for wages, there is a positive marriage premium and an intermarriage penalty. One explanation for the marriage premium could be the fact that the average age for both sample years of these immigrants is between 42-45 years for 1970, and 34-36 for 1980. More precisely, if these women have own children, these children are possibly old enough to provide help with the household chores and raising younger siblings. This additional help could take away part of the effort for the mothers. As they do not need to put so much effort and labor within the household, these women could improve their performance at work, allowing them to earn higher wages than their single counterparts. It is important to emphasize that foreign females could have different work patterns and household experiences than the American-born females. In addition, both the OLS results and the Heckman results show a wage penalty for immigrants who are married to US-born spouses relative to those married to foreign-born spouses. One possible explanation for this penalty is that unlike the endogamous group, intermarried females do not face the pressure to increase their productivity and performance on the job.[31] In light of the family investment hypothesis, an additional explanation of this result could focus on the endogamous group. Non-intermarried females might need to be more productive or take higher paying jobs than their intermarried counterparts in order to support their husband's investments in human capital.

4. Probability of Intermarriage and 2SLS Regression results

Table 7 in the Appendix shows the multinomial logistic regression results for the probability of being intermarried for the exogamous and endogamous groups.[32] Most coefficient estimates have the expected signs and are statistically significant in difference from zero. The probability of intermarriage is an increasing and concave function of age since the coefficient estimate on age is positive and the coefficient on the squared term of age is negative for both groups. Relative to singles, more years of schooling increases the probability of marrying exogamously and lowers the probability of being endogamously married. Relative to being born in Europe, which is the omitted category, being born in any other region but North America lowers the probability of being exogamously married relative to being single. Relative to being born in Europe, being born in any other region but Central America and the Caribbean lowers

31 As Table 3 shows, intermarried females enjoy both higher average husband's income and higher total family incomes than the non-intermarried immigrants.

32 The reference category is singles.

the probability of being exogamously married relative to being single. Relative to living in the Northeast, which is the omitted category, living in any other region increases the probability of being exogamously married relative to being single and lowers the probability of being endogamously married relative to being single. Relative to being White, which is the omitted category, being Black and Asian lowers the probability of being intermarried relative to being single, while belonging to other races increases the probability of being intermarried relative to being single. Relative to being White, being Black and Other race lowers the probability of being endogamously married relative to single, while being Asian increases the probability of being endogamously married relative to being single. Spending more years in the United States increases both the probability of being intermarried and being non-intermarried relative to being single. Higher values for the sex ratio increases the probability of being intermarried and being endogamously married relative to being single. The relative availability of marriage partners from own ethnic group decreases the probability of being married to a native relative to not being married at all and increases the probability of being married to a foreigner relative to being single.

In the 2SLS procedure, the decisions to marry and intermarry are treated as endogenous. The results are shown in Table 5. Most coefficient estimates are not statistically significant in difference from zero. I am only going to focus on the coefficient estimates on the marriage indicators and the years spent in the United States. Although none of these three coefficient estimates is statistically significant in difference from zero, I am going to discuss their economic significance. First, the marriage premium entirely disappears and becomes a marriage penalty of over 100%. Second, the intermarriage penalty is still negative and it more than triples in size. Third, the coefficient estimate on years spent in the Untied States remains positive, suggesting an assimilation effect of spending more time in the host country.

5. Specification Check: Relaxing the Non-English Speaking Criterion

The regression results when the restriction that immigrants should come from a non-English speaking country (NESC) is relaxed are shown in Table 8 in the Appendix. They serve as a specification check and do not show any fundamental differences with the NESC results. The coefficient estimate on the marriage premium is positive and statistically significant in difference from zero from the OLS and Heckman results, and is negative and insignificant from the 2SLS results, which is similar to the NESC results. The intermarriage income penalty is statistically significant in difference from zero from the OLS and Heckman results and is negative and insignificant from the 2SLS results, which is similar to the NESC results. The dummy variable for English speaking country is negative and not statistically significant in difference from zero from all three specifications. The years in the United States variable is still positive but not statistically significant in difference from zero. Both assimilation variables are not statistically significant in difference from zero, indicating that adding the English-speaking immigrants to the sample diminishes the relative importance of the assimilation variables for the wage equation. Most of the coefficient estimates on the rest of the included independent variables are similar to the NESC sample regression results.

6. Specification Check: English-Speaking Immigrant Husbands

As an additional model specification check, I included a dummy variable for the native English-speaking husbands of the endogamously married females. The results in Table 9 in the Appendix do not show any major differences from the previous specifications. Some results are worth addressing. The marriage premium is still positive and significant from the OLS and Heckman results and negative and not statistically significant in difference from zero from the 2SLS. It increases more than four times when the Heckman estimation is used. The intermarriage premium is still negative but is not statistically significant in difference from zero from the 2SLS results. The coefficient estimate on the assimilation variable years in the US is statistically significant in difference from zero only from the Heckman results. The coefficient estimate on whether the immigrant female came from an English-speaking country is negative and not statistically significant in difference from zero from all three specifications. The dummy variable on whether the husband of the endogamously married female came from an English-speaking country is negative and statistically significant in difference from zero from the OLS results and positive and insignificant in difference from zero from the Heckman and 2SLS results. This provides only poor evidence on the effects of language on the assimilation dynamics and earnings of immigrants.

7. Further Discussion of Results

The differences between the Heckman method and the OLS are practically small and are most likely due to the fact that the coefficient estimate on lambda is not statistically significant in difference from zero. The Heckman results and the 2SLS results differ significantly. On the one hand, this is due to the fact that they correct for different sources of bias, i.e. the Heckman procedure corrects for selection bias while the 2SLS corrects for endogeneity.[33],[34] Both estimation techniques provide consistent estimates in large samples. The Heckman results are not as efficient as maximum likelihood estimates. The 2SLS have increased variances and standard errors, which may explain the statistically insignificant in difference from zero results. In addition, if the fit of the reduced form equation is relatively poor, then 2SLS estimators will be still biased. The difference in the results from the Heckman and the 2SLS procedures could also be reflective of a poor choice of instruments for the 2SLS estimation. Given the shortcomings, the Heckman results may be better estimates of the true population parameters. A potentially superior estimation method will be a sample selection model with a common dummy endogenous regressor in simultaneous equations. While this estimation technique will allow us to tackle both sources of bias simultaneously, it may be econometrically challenging. Particularly challenging aspects of this estimation technique may involve establishing the sampling distribution of the estimators and obtaining consistent and efficient coefficient estimates.

V. CONCLUSION

This paper investigated whether female immigrants married to US-born spouses (i.e. exogamously married immigrants) have higher earnings than female immigrants married to other immigrants (i.e. endogamously married immigrants). I find that there is a marriage premium that is positive and statistically significant in difference from zero even when I correct for the labor force selection bias. One explanation for this premium could be that married female immigrants have older children at home who can take care of the household and release the burden on the mothers. This could make these married foreign females more productive at work. In addition, I find that exogamously married immigrants receive an intermarriage penalty. My results show that there is a negative selection bias in the labor force among female immigrants. In other words, higher human capital immigrants are not working for wages. At the same time, among those who are working for wages, there is a positive marriage premium and an intermarriage penalty. When I correct for

33 The 2SLS also corrects for simultaneity, or the fact that intermarriage can be both a cause and a result of economic assimilation of immigrants.

34 The Heckman procedure deals with the problem that selection bias causes the error term to be correlated with an explanatory variable (Kennedy, 2003). The Heckman estimates the probability of being in the labor force first on the basis of a probit model and generates the Inverse Mills Ratio, which is used as an additional regressor in the earnings equation (Gujarati, 22003). The Heckman estimator is consistent but not as fully efficient as the maximum likelihood estimates (Kennedy, 2003; Kantarevic, 2004). 2SLS sweeps clean the dependent variable of the influence of the error term by obtaining the estimator of Y from the reduced-form equation and then replacing it in the original equation to produce consistent estimates (Gujarati, 2003).

the endogeneity of the marriage decision, I find that that exogamously married female immigrants still receive a penalty relative to exogamously married immigrants. This premium is economically significant but not statistically significant in difference from zero and no meaningful interpretations of it can be done. The negative premium could be due to the fact that unlike their exogamous counterparts, non-intermarried females do not enjoy the same high husband's income and husband's social networks. Their motivation to perform better on the job, therefore, could be stronger than that of the intermarried.

These results contrast the findings of Meng and Gregory (2005) and Meng and Deurs (2006) for Australia and France, respectively, who find positive, significant, and robust intermarriage premiums among immigrants. Kantarevic (2004) finds a male intermarriage premium of about 2.5 %, which disappears once the specification controls are introduced.

Given that the intermarriage literature is in its infancy, many interesting empirical questions arise. In particular, further investigations of the marriage premium among immigrant females could be done. Finding an alternative estimation technique that will allow to handle both the selection bias and the endogeneity simultaneously may be superior but econometrically challenging. In addition, if data availability permits, the intermarriage premium could be studied across different countries over time. Finding a different data might allow for fixed and random effects, as well as adding occupational dummy variables to account for some of the variation in the marriage premium. The cross-generational effects, i.e. what happens to the premium in for the descendants of the endogamously married and endogamously married females are still questions that remain unanswered.

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APPENDIX

Table 1

Variable	Description	Further Explanation
Y	Log real hourly wage in 2000 constant US dollars in year t	
Married	Indicator variable for marriage, 1=married, 0=single	
Exogamous	An interaction variable of two indicator variables. When Married=1, then Exogamous=1 for exogamously married individuals, Exogamous=0 otherwise	When included in the regression together with married, the coefficient estimate on this dummy variable captures the difference between the exogamous and endogamous groups. It helps to think of this dummy as a special interaction term (married*exogamous), which is exactly identical with the dummy exogamous in this particular case.
H	A vector of human capital and demographic variables including age, age squared, years of schooling, four indicator variables for race, seven indicator variables for birthplace, five indicator variables for place of residence	The squared term of age was later divided by 1000 to avoid scaling effects; the indicators for Race include Black, Asian, Other (White is the control group), indicator variables for birthplace – North America, South America, Central America and the Caribbean, Asia, Africa, Other (Europe is the control group), indicator variables for place of residence - West, South, Midwest (North East is the control group)
A	Assimilation variable: years since migration	Years since migration squared was dropped due to collinearity
Dum 1980	Dummy variable =1 if year=1980 =0 if year=1970	
□	Error term	

Table 6 Heckman Regression Results

	Probit Coeff Estimates
Married	-0.312***
	(0.022)
Exogamous	-0.057**
	(0.024)
Age	0.142***
	(0.004)
Age Squared	-1.789***
	(0.050)
Education	0.048***
	(0.002)
Born N. America	0.063
	(0.148)
Born S. America	-0.072*
	(0.038)
Born C. America -Caribbean	0.011
	(0.022)
Born Asia	-0.106***
	(0.039)
Born Africa	-0.187**
	(0.082)
Born Other	-0.174***
	(0.033)
Midwest	0.011
	(0.024)
South	-0.028
	(0.023)
West	-0.008
	(0.021)
Black	0.057*
	(0.033)
Asian	0.141***
	(0.043)
Other race	0.029
	(0.060)
Years in the Untied States	-0.004***
	(0.001)
Indicator Year 1980	0.054***
	(0.018)
Number Children <5 Yrs	-0.458***
	(0.018)
Number Children 5-18 Yrs	-0.148***
	(0.009)
Constant	-2.790***
	(0.074)

Table 7: Probability of Interethnic Marriage

	Exogamous	Endogamous
Age	0.329***	0.307***
	(0.015)	(0.014)
Age Squared	-5.073***	-4.387***
	(0.200)	(0.184)
Education	3.348e-02***	-3.706e-02***
	(7.582e-03)	(6.448e-03)
Born N. America	0.296	-0.084
	(0.435)	(0.521)
Born S. America	-0.094	-0.447***
	(0.135)	(0.125)
Born C. America -Caribbean	-0.141*	0.287***
	(0.078)	(0.070)
Born Asia	-0.048	-0.216*
	(0.121)	(0.130)
Born Africa	-0.075	-0.188
	(0.257)	(0.294)
Born Other	-0.349***	-0.021
	(0.108)	(0.109)
Midwest	0.076	-0.021
	(0.076)	(0.075)
South	0.170**	-0.516***
	(0.075)	(0.076)
West	0.077	-0.270***
	(0.068)	(0.064)
Black	-0.460***	-0.635***
	(0.124)	(0.107)
Asian	-0.229	0.796***
	(0.139)	(0.131)
Other race	0.147	-0.250
	(0.196)	(0.193)
Years in the Untied States	0.128***	0.020***
	(0.008)	(0.008)
Years in the United States Squared	-0.000***	0.001***
	(0.000)	(0.000)
dum1980	-0.350***	0.015
	(0.059)	(0.058)
Sex Ratio	0.001	0.001**
	(0.001)	(0.001)
Prob Marry Within Own Ethnic Group	-8.899***	6.717***
	(1.773)	(1.024)
Constant	-7.895***	-5.925***
	(0.280)	(0.262)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Regression Results with English-speaking immigrants

Core Regressors	OLS	Heckman	2SLS
Married	0.051***	0.065***	-1.080
	(0.014)	(0.016)	(1.535)
Exogamous	-0.055***	-0.055***	-0.245
	(0.016)	(0.016)	(0.694)
Age	4.244e-02***	3.944e-02***	1.104e-01
	-2.58E-03	(3.161e-03)	(1.045e-01)
Age Squared	-0.467***	-0.430***	-1.449
	(0.032)	(0.039)	(1.515)
English Speaking Country	-0.015	-0.018	-0.044
	(0.017)	(0.017)	(0.037)
Education	0.045***	0.044***	0.045***
	(0.002)	(0.002)	(0.003)
Born N. America	0.005	0.006	0.035
	(0.021)	(0.021)	(0.070)
Born S. America	0.004	0.005	-0.056
	(0.026)	(0.026)	(0.083)
Born C. America -Caribbean	-0.038**	-0.037**	-0.049
	(0.015)	(0.015)	(0.046)
Born Asia	0.036	0.039	0.015
	(0.030)	(0.030)	(0.047)
Born Africa	0.114	0.120	0.065
	(0.075)	(0.075)	(0.110)
Born Other	-0.056**	-0.052**	-0.111
	(0.024)	(0.025)	(0.093)
Midwest	-0.031**	-0.030**	-0.011
	(0.015)	(0.015)	(0.045)
South	-0.145***	-0.144***	-0.152***
	(0.015)	(0.015)	(0.027)
West	-0.051***	-0.050***	-0.065***
	(0.013)	(0.013)	(0.022)
Black	0.057**	0.057**	-0.063
	(0.023)	(0.023)	(0.175)
Asian	0.041	0.038	0.091
	(0.031)	(0.031)	(0.063)
Other race	-0.011	-0.012	-0.038
	(0.043)	(0.043)	(0.063)
Years in the Untied States	0.001	0.001*	0.017
	(0.001)	(0.001)	(0.026)
Indicator Year 1980	-0.191***	-0.192***	-0.250**
	(0.011)	(0.011)	(0.097)
Constant	0.940***	1.039***	0.170
	(0.053)	(0.080)	(1.235)
Observations	16,992	16,992	16,992
Censored Observations	0	18,932	
Ajudsted R-squared	0.12		
rho		-0.068	
		0.041	
sigma		0.633	
		0.005	
lambda		-0.043	
		0.026	

(1)Note: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

(2)English-speaking countries are Canada, the UK, Australia and New Zealand.

Table 9: Regression results with English-speaking immigrants and English-speaking immigrant husbands

Core Regressors	OLS	Heckman	2SLS
Married	0.058***	0.253***	-1.073
	-0.014	(0.026)	(1.518)
Exogamous	-0.064***	-0.104***	-0.241
	-0.017	(0.030)	(0.690)
Age	4.212e-02***	3.677e-02***	1.101e-01
	-2.58E-03	(4.534e-03)	(1.036e-01)
Age Squared	-0.464***	-0.302***	-1.442
	-0.032	(0.057)	(1.501)
Education	0.045***	0.010***	0.045***
	-0.002	(0.003)	(0.003)
Born N. America	0.004	-0.092**	0.036
	-0.021	(0.036)	(0.070)
Born S. America	0.004	-0.005	-0.056
	-0.026	(0.045)	(0.082)
Born C. America-Caribbean	-0.039***	-0.079***	-0.048
	-0.015	(0.026)	(0.046)
Born Asia	0.037	0.039	0.015
	-0.03	(0.050)	(0.046)
Born Africa	0.114	0.187*	0.066
	-0.075	(0.112)	(0.109)
Born Other	-0.056**	-0.013	-0.111
	-0.024	(0.040)	(0.093)
Midwest	-0.032**	-0.006	-0.011
	-0.015	(0.026)	(0.045)
South	-0.146***	-0.098***	-0.152***
	-0.015	(0.026)	(0.026)
West	-0.052***	-0.101***	-0.065***
	-0.013	(0.022)	(0.021)
Black	0.056**	0.036	-0.062
	-0.023	(0.038)	(0.173)
Asian	0.039	0.032	0.092
	-0.031	(0.053)	(0.063)
Other race	-0.011	-0.009	-0.038
	-0.043	(0.069)	(0.063)
Years in the United States	0.001	0.005***	0.017
	-0.001	(0.001)	(0.026)
English Speaking Country	-0.005	0.001	-0.050
	-0.017	(0.030)	(0.048)
Husband English Speaking Country	-0.094***	0.060	0.055
	-0.035	(0.059)	(0.148)
dum1980	-0.192***	-0.112***	-0.249***
	-0.011	(0.019)	(0.096)
Constant	0.949***	1.436***	0.171
	-0.053	(0.098)	(1.230)
Observations	16,992		16,992
Censored	0	14,168	0
Adjusted R-squared	0.12		
rho		-0.886	
		0.008	
sigma		1.389	
		0.010	
lambda		-1.230	
		0.018	

(1) Note: Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

(2)The English-speaking husbands are non-US born

Industry Structure Similarities, Trade Agreements, and Business Cycle Synchronization

Samuel Marll

Abstract

This paper analyzes the effects of industry structure similarities, free trade agreements, and geographic borders on regional business cycle correlation, using fifty US states, 10 Canadian provinces, and 1 Canadian territory as a case study. Using two cross-sectional OLS regressions and one panel data OLS regression, this study finds that pair-wise gross territorial product growth correlation decreased significantly after NAFTA ratification for state-state, province-province, and state-province territorial pairs, contrary to previous literature's results. NAFTA effectively decoupled intra-national business cycles in the US and Canada while also desynchronizing cross-border pair-wise GSP growth correlation, but cross-border pair-wise GSP growth correlation was much less desynchronized post-NAFTA relative to intra-national pairs. These results indicate that NAFTA and the US-Canada border may produce two opposing forces that dampen each other's desynchronizing effects.

Introduction

The United States and Canada have a unique economic relationship. Sharing the longest unfortified border in the world, similar cultures, and a common language, the two nations are each others' largest trading partners. US-Canada goods trade increased dramatically after 1988, when the Canada-United States Free Trade Agreement (CUSFTA) was ratified, eliminating tariffs on most trans-border goods trade. 1994 witnessed the ratification of the North American Free Trade Agreement (NAFTA), superseding CUSFTA. NAFTA's immediate effects were to reduce or eliminate the majority of remaining tariffs on motor vehicles, computers, textiles, agriculture, and other commodities between the US, Canada, and Mexico. With tariffs and barriers removed, goods trade in these sectors increased appreciably from 1994 to 2004, jumping 110.1% over a period of ten years. As of 2007, exports and imports to and from the US constitute 81% and 67% of total Canadian exports and imports, respectively, while exports and imports from Canada comprise 23% and 17% of total US exports and imports.

This astronomical rise in US-Canada goods trade, spurred by advances in North American economic integration, is hotly debated in Canadian policy circles. Opponents of the two trade agreements argue that further economic integration will tighten alignment of the Canadian business cycle with that of the US due to increased trans-border goods flows and bind growth in export-driven sectors of the Canadian economy to developments in American markets. Blayne Haggart, a research analyst reporting to Canadian Parliament, voiced concerns that "Greater economic integration will lead to the dissolution of Canada (2001)". The monetary economist Thomas Courchene also noted in his empirical research that "We are witnessing the rise of 'region-states', where geographic regions trade within their own area (2000)". This scenario culminates in Canada's economic degeneration into a market integrally linked to developments in US goods and asset markets.

Answering the question of whether trade agreements and industry structure similarity synchronize regional business cycles would determine whether North American trade integration is inextricably tying Canadian goods markets to those of the US. This paper analyzes the effects of industry structure similarity, the US-Canada border, and NAFTA ratification on synchronicity of regional US and Canadian economic growth from 1984 to 2004. The analysis finds that GDP growth correlation at the state and provincial level decreased significantly after NAFTA ratification. Agriculture and mining industry structure similarities were found to have strongly positive and statistically significant impacts on GSP growth correlation. Convergence of industry structure similarity in these two sectors increases predicted GSP growth correlation appreciably. Manufacturing industry structure similarity was not found to be a statistically significant determinant.

Prior to NAFTA ratification, the border weakened predicted cross-border pair-wise correlation by 31.4%. However, NAFTA and the border may have produced two opposing channels that served to dampen the desynchronizing effect. After NAFTA ratification, the border desynchronized cross-border pairs by only 13.7%. NAFTA's deregulatory effects may have spurred increases in intra-industry trade volume between states and provinces that were not possible between intra-national pairs.

Intra-nationally, NAFTA desynchronized state-state and province-province pairs by 24.1%. The border dampened NAFTA's desynchronizing effect to some extent, with cross-border pairs' predicted correlation coefficients reduced by only 6.4%. The geographic border and NAFTA ratification negate each other's desynchronizing forces to some extent, leaving post-NAFTA intra-national business cycles much more strongly desynchronized than post-NAFTA cross-border business cycles. All regional business cycles were desynchronized, but NAFTA impacted intra-national pairs much more strongly than cross-border pairs.

Literature Review

In a theoretical context, the impact of increased goods trade on business cycle synchronization is ambiguous. Assuming demand-side shocks drive business cycles, inter-industry trade increases between country pairs should channel the effects of these shocks from one country to another, leading to an increase in business cycle correlation as trade increases. For example, positive shocks to an economy could lead to increased income, subsequently increasing demand for imports from another economy, accelerating economic growth in the second country via export-led growth. The magnitude of the shock's transmission to the second economy would presumably be positively correlated with the level of trade between the two.

This conclusion rests on the assumption that the increases in trade are not intra-industrial, and that economies' production structures do not become more similar as a result. Krugman (1993) argues that as trade integration progresses, countries specialize in production of specific outputs. Therefore, trade integration that induces asymmetric industry specialization should desynchronize business cycles. We can alternatively assume that shocks are specific to distinct industries within the economy, which may have offsetting effects.

If increases in trade are intra-industrial, and economies' production structures become increasingly similar as trade increases, then with business cycles dominated by industry-specific shocks, trade integration that increases intra-industry trade should lead to increased synchronization of business cycles, due to the more symmetric response of economies to shocks. Frankel and Rose (1998) assert that the nature of trade integration and international trade can cause business cycles to converge or diverge. They argue that "closer international trade could result in tighter or looser correlations of national business cycles". Per the Ricardian theory of comparative advantage, closer inter-industry trade linkages could result in industry specialization, sensitizing economies to industry-specific shocks, thereby leading to more idiosyncratic business cycles. If intra-industry trade predominates, then industry-specific shocks will create identical responses within economies, synchronizing economic growth.

Preferential trade agreements' effect on business cycle correlation is a topic that has been explored extensively by European economists, in the wake of politicoeconomic integration on that continent. While this research has extensively studied the ramifications of trade agreements and currency unions for European and Asian markets, there is considerably less research detailing trade agreements' impact on US and Canadian goods markets. This paper fills that gap by studying the effect NAFTA has on state-level economic growth correlation and intra-industry goods trade.

Fiess (2007) employs OLS regression and spectral analysis to quantify the degree of business cycle correlation between Central American nations and the United States in the wake of the Dominican Republic-Central American Free Trade Agreement (DR-CAFTA). Using band-pass filtered annual data from 1965 to 2002 for 16 Central American nations, along with monthly data on Central American industrial production for 1995 to 2002 (due to a scarcity of reliable data for Central American economic activity), he determines the extent to which Central American economies are synchronized. Fiess discovers that Central American sensitivity to US economic activity has increased over time, while the period of relative tranquility in the 1990s increased synchronization within Central America. Using a cross-plot of bilateral exports to GDP ratios and business cycle coherence, there no evidence of a positive relationship between trade intensity and business cycle synchronization. Fiess's paper provides new information regarding the effects of free trade agreements on developing countries, specifically those in the Central American region. His OLS regression also provides a framework for analyzing the US economy's effect on other nations, and its effect on trade linkages between other country pairs.

Böwer and Guillemineau (2006) analyze the extent of business cycle correlation in the EU. Using extreme-bounds analysis (EBA), they examine the transmission mechanism for increased business cycle synchronization within the European Monetary Union. Using a vector of coefficients of bilateral business cycle correlations for twelve euro area countries, they regress this vector on an exogenous variable of interest with a varying set of 1-3 control variables, along with gravity theory model variables. From there, they identify extreme bounds by generating the lowest and highest values of confidence intervals for the estimated parameter on the exogenous variable of interest. If the low and high bounds on the interval have the same qualitative sign, and the parameter estimate is significant in all regressions, the variable is regarded as robust.

They find a positive correlation between bilateral trade and the vector of correlation coefficients, as well as for the bilateral trade to GDP ratio. Bilateral trade only explains approximately 10% of GDP correlation. Trade openness is found to have a positive but statistically insignificant effect on business cycle synchronization. Trade specialization also fails to qualify as robust for the 1980 to 1996 period, but becomes robust for 1997 to 2004. The majority of the impact on cycle synchronization appears to come from specialization in machinery and transport equipment. They also find a negative relationship between economic specialization and cycle correlation, but with a low R^2 of the regression, the authors conclude that similarity in relative shares of economic specialization says little about cycle correlation. Böwer and Guillemineau report that external trade is a key determinant of cycle synchronization for the euro zone. They find an endogeneity effect for optimal currency areas: If trade promotes co-movement of cycles, then a common currency that fosters trade leads to increasingly synchronized cycles within the monetary union. Increases in intra-industry trade also lead to increased synchronization, judging by its status as a robust determinant of cycle correlation in the 1997-2004 period for the extreme bounds analysis.

Chiquiar and Ramos-Francia (2005) analyze the effect of NAFTA on commercial integration of industrial and developing countries—in this case, the United States and Mexico. They analyze two components of this issue: First, whether NAFTA enhanced business cycle synchronization between Mexico and US, and second, whether increased competition from other countries (whose main advantage is an abundance of unskilled labor) undermined synchronicity of US and Mexican business cycles. The authors use spectral analysis, cointegration tests, and Granger causality tests to examine this. The spectral analysis focuses on manufacturing output behavior for the US and Mexico at business-cycle frequencies. Using differenced logs of quarterly manufacturing production indices for Mexico and the US from 1980 to 1993, they estimate the coherence between these differenced logs. The spectral analyses find statistically significant coherence estimates for bands of cycles with periods from two to eight years. This corresponds to the average length of business cycles. For 1996 to 2004, the coherence tests are run again, and coherences are significantly stronger for the post-NAFTA period, implying stronger US-Mexico business cycle correlation, and more cointegrated manufacturing production levels between the two nations.

Mexico-US cross correlation patterns in manufacturing output pre- and post-NAFTA are also analyzed. Tests indicate that before NAFTA implementation, cyclical movements in US output lead Mexico's cycle by two years. After 1996, that lag period decreased, indicating a shift to a non-lagged contemporaneous correlation between manufacturing output cycles. The authors find no evidence of cointegration for the pre-NAFTA period, but do find evidence for cointegration in the NAFTA period. This suggests Mexican cointegration with US manufacturing industries in the wake of NAFTA implementation, leading to higher business cycle synchronization. Granger causality tests indicate causation is unidirectional from US manufacturing production to Mexico's. Instead of examining US-Mexican output correlation directly, Chiquiar and Ramos-Francia examine manufacturing synchronization, an industry comprising a significant share of output for both nations. By testing the extent of manufacturing industry correlation between nations, they can determine how manufacturing shocks affect cycle synchronization for both nations. Chiquiar's paper explains how trade agreements impact a sector of the intermediate goods market in North America. The methodology of this paper hinges on the assumption that industry-specific shocks (in this case, shocks to manufacturing) drive business cycle fluctuations. If cycle fluctuations are demand-driven rather than industry-driven, the usefulness of this analysis may be limited.

Cortinhas (2007) studies the effects of intra-industry trade and industry specialization on Southeast Asian business cycle synchronization. He uses annual data for real GDP of the five ASEAN nations from 1962 to 1996. Cortinhas excludes post-1997 data, to avoid the East Asian financial crisis's distorting effects on the data. Initial OLS and 2SLS empirical results suggest a positive correlation between intra-industry trade and cycle synchronization. Cortinhas runs a second OLS regression, this time regressing the gap in real output growth between country pairs on an index measuring intra-industry trade. The parameter on intra-industry trade becomes negative, indicating an increase in intra-industry trade will in fact reduce real output growth gaps between ASEAN nations. This estimate is consistent with the positive parameter on IIT in the first regression. Cortinhas then runs a second 2SLS to control for endogeneity, using the same instruments as before, and finds that the parameter on intra-industry trade is significant in synchronizing ASEAN business cycles at the 1% level. Ultimately, Cortinhas concludes that intra-industry trade is a significant, robust variable in determining ASEAN cycle correlation. He argues that the costs of joining a currency union in ASEAN decreases as intra-industry trade increases.

This paper uses OLS regression analysis to measure the effects of NAFTA on the correlation of state and provincial level economic growth. Instead of examining NAFTA's effects at a macro level, this analysis uses state and provincial data to capture the effects of physical distance, intra-industry trade in agriculture, manufacturing, and mining, and the geographic border at a microeconomic level. This model can be viewed as a variant of the gravity model of trade, since it incorporates control variables for physical distance and trade flows. The correlation coefficient of gross state product growth between two territories is calculated for all possible pairs of 50 states, 10 provinces, and 1 territory, generating 1,830 observations. This correlation coefficient is regressed on variables including state/province population levels, distance between most populous cities, exports as a share of gross state product, industry structure similarity within the mining, agriculture, and manufacturing sectors, and a set of dummies and interaction terms representing the geographic border and NAFTA ratification. This methodology allows us to measure the effects of NAFTA on not only state and provincial level economies, but also on sectors of the economy producing highly tradable output, an approach not utilized in the aggregate-level analyses of previous literature.

Methodology

The regression equation appears below:

$$\boldsymbol{\rho_{I,J} = \beta_0 + \beta_1 \text{Agriculture Sector Similarity}_{I,J} + \beta_2 \text{Manufacturing Sector Similarity}_{I,J} + \beta_3 \text{Mining Sector Similarity}_{I,J} + \beta_4 \ln(\text{Population}_I) + \beta_5 \ln(\text{Population}_J) + \beta_6 \ln(\text{Distance}_{I,J}) + \beta_7 \text{Border}_{I,J} + \beta_8 \text{NAFTA}_t + \beta_9 (\text{Exports/GSP}_I) + \beta_{10} (\text{Exports/GSP}_J) + \varepsilon_{I,J}}$$

$\rho_{I,J}$ is a correlation coefficient measuring the degree of linear association between the GSP growth rate of state/province *I* and the GSP growth rate of state/province *J*. With this dependent variable, we can measure the synchronicity between territory *I*'s annual economic growth and that of all other territories. Data was taken from the Bureau of Economic Analysis and Statistics Canada. Provincial economic data is restricted to 1984 forward, so the scope of the analysis is limited to the years 1984 to 2004.

The first three regressors are variables measuring the degree of industry structure similarity between territory *I* and all other states and provinces, in the agriculture, mining, and manufacturing sectors. Interstate export and import data is not collected by US statistical agencies, so direct measures of intra-national and intra-industry exports and imports as shares of states'

GSP are infeasible. Using BEA and Statistics Canada data, we instead measure industry structure similarities between territory pairs. For two given states *I* and *J*, agriculture, mining, and manufacturing as a share of each territory's GSP are taken, and averaged over the time period in question, giving us six separate values for states *I* and *J* containing their respective average shares of agriculture, mining, and manufacturing for the time period.

With these six separate values, the values representing state *J*'s GSP shares are subtracted from the values representing state *I*'s GSP shares, and then the absolute value is taken, giving us 3 variables measuring, as a share of GSP, the deviation in industry similarity between state *I* and state *J* for agriculture, mining, and manufacturing. This set of deviations is computed between state *I* and all 61 territories in the analysis. Trade theory states that as the deviation between two territories' industry as a share of GSP increases, their level of intra-industry trade should decrease. With lower levels of intra-industry trade, the two territories' responses to industry-driven economic shocks become increasingly asymmetrical. As a result, we expect the signs on these three intra-industry trade variables' coefficients to be negative.

Two population variables are also regressors. The first population variable corresponds to the log of territory *I*'s average population over the time period of the data set. The second population variable measures the log of territory *J*'s average population over the span of the data set. Previous literature on population's effect on cycle correlation is scarce, but if increases in consumer population generate higher demand for tradable output, intra-industry trade volume will inflate and synchronize pair-wise territories. Additionally, more populous territories should be more economically diversified, stabilizing yearly GSP growth. This may affect cycle correlation with other territories. Thus, the coefficients on the population vectors should be positive. The regression model includes a distance regressor, corresponding to the log of the distance between territory *I*'s most populous city, and the most populous city in territory *J*. The gravity model of trade states that as the distance between territories increases, the cost and time necessary to conduct goods trade increases, decreasing the predicted amount of total trade. Therefore, we expect the distance regressor's sign to be negative.

The border dummy quantifies the effect of the geographic border on business cycle correlation. Each entry in this variable corresponds to a pairing between territory *I* and all other territories, registering "0" for intra-national pairings, and "1" for pairings that cross the border. International finance theory argues that border barriers such as tariffs, customs checkpoints, and trade restrictions reduce trans-border trade volume. With reduced levels of intra-industry goods trade, industry-driven shocks will trigger increasingly asymmetrical responses to state and province pairs. Thus, the coefficient on the border dummy should be negative.

Two export variables were included, to estimate the effects of export-dependent economies on GSP correlation. The first export variable measures international exports as a share of the first territory's gross state product. The second measures the same for the second territory's GSP. As international exports as a share of GSP increases, state and province-level economies' annual growth becomes increasingly variant, as fluctuations in the international goods market accelerates or depresses export-led growth. If exports as a share of gross state product increase, a state-level economy would become increasingly tied to developments in other territories' goods markets. Therefore, we expect the coefficient estimates on these variables to be positive. International export data for states was not recorded until 1999, so estimates for these variables are restricted to the post-NAFTA regression.

The NAFTA dummy registers "0" for observations measured in the 1984-1993 pre-NAFTA dataset, and "1" for observations taken in the 1994-2004 post-NAFTA dataset. NAFTA's primary effect was to eliminate all remaining tariffs on tradable output in several sectors of the Canadian and US economies. With intra-industry trade volume increasing in these newly deregulated sectors, and assuming macroeconomic shocks are industry specific, we expect NAFTA to increase pair-wise correlation coefficients.

These vectors are computed for every territory in the analysis, giving us 60 different sets of observations. These sets are then combined into one large set of observations, creating a final group of nine regressors with 1,830 entries each. See the following table for summary statistics of the variables.

Pre-NAFTA (1984-1993)				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Correlation i, J	0.397845	0.354456	-0.71519	0.981224
Agriculture Similarity i, J	0.026751	0.027623	1.85E-06	0.114372
Mining Similarity i, J	0.062572	0.085288	4.67E-06	0.348355
Manufacturing Similarity i, J	0.107517	0.113824	0.000192	0.780746
Ln (Distance i, J)	7.418351	0.775738	2.755334	9.142286
Ln (Population i)	3.571408	0.609343	2.679153	6.994147
Ln (Population J)	4.296975	1.31007	2.679153	6.994147

Post-NAFTA (1994-2004)				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Correlation i, J	0.238658	0.360051	-0.81859	0.995907
Agriculture Similarity i, J	0.021462	0.021531	-0.00554	0.091592
Mining Similarity i, J	0.047482	0.066825	-0.01866	0.238547
Manufacturing Similarity i, J	0.071065	0.052567	-0.06749	0.290645
Ln (Population i)	3.623514	0.605917	2.687775	7.063507
Ln (Population J)	4.339703	1.307634	2.687775	7.063507
(Exports/GSP i)	0.065764	0.046117	0.010517	0.384355
(Exports/GSP J)	0.125679	0.105129	0.010517	0.384355

Pooled (1984-2004)				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Correlation i, J	0.318252	0.365978	-0.81859	0.995907
Agriculture Similarity i, J	0.024106	0.024903	-0.00554	0.114372
Mining Similarity i, J	0.055027	0.076975	-0.01866	0.348355
Manufacturing Similarity i, J	0.089291	0.090497	-0.06749	0.780746
Ln (Population i)	3.597461	0.608108	2.679153	7.063507
Ln (Population J)	4.318339	1.308848	2.679153	7.063507

Table 1. Summary statistics for the variables in the OLS analyses.

Conventional standard errors are insufficient for this type of regression analysis. Heteroskedasticity in the error term is typical for cross-sectional regressions dealing with state-level economic data. Additionally, autocorrelation in the error term is a likely problem. Typically, serial correlation is not a problem for cross-sectional data, as there exists no temporal pattern within the residuals. However, spatial autocorrelation may be at work in the residuals. If there is an economic component unique to a single state affecting its GSP growth, all observations including that territory within the pair will suffer from correlation of the residual term. Thus, spatial autocorrelation is likely present. To simultaneously correct for heteroskedasticity and spatial autocorrelation in the error term, heteroskedasticity and autocorrelation consistent standard errors were employed.

Three separate versions of the regression were run. The first regression dropped the entries with a "1" for the NAFTA dummy, giving us coefficient estimates for the model prior to NAFTA ratification. The second excluded all pre-NAFTA observations, giving the sample regression function for the post-NAFTA era. Finally, a panel data regression was run, with all entries included, allowing us to see the coefficient estimates for the overall time period of 1984 to 2004. With variation in the NAFTA dummy, the pooled regression allowed estimation of the NAFTA dummy coefficient, quantifying NAFTA's synchronizing or desynchronizing effects on state-level business cycle synchronization. To capture the effect of the border pre- and post-NAFTA, the NAFTA and border dummies were interacted with each other, and included in the pooled cross-sectional regression, creating the below regression model:

$$\boldsymbol{\rho_{I,J\,t} = \beta_0 + \beta_1 \text{Agriculture Sector Similarity}_{I,J\,t} + \beta_2 \text{Manufacturing Sector Similarity}_{I,J\,t} + \beta_3 \text{Mining Sector Similarity}_{I,J\,t} + \beta_4 \ln(\text{Population}_{I\,t}) + \beta_5 \ln(\text{Population}_{J\,t}) + \beta_6 \ln(\text{Distance}_{I,J}) + \beta_7 \text{Border}_{I,J} + \beta_8 \text{NAFTA}_{t} + \beta_9 (\text{NAFTA}_{t} * \text{Border}_{I,J}) + \varepsilon_{I,J\,t}}$$

Empirical Results and Discussion

Regressor	*n = 1,830 Pre-NAFTA Coefficient*	*n = 1,830 Post-NAFTA Coefficient*	*n = 3,660 Panel Coefficient*
Agriculture Industry Similarity	-1.546*** (0.304)	-0.849** (0.360)	-1.165*** (0.245)
Manufacturing Industry Similarity	0.121* (0.069)	-0.990*** (0.201)	-0.093 (0.077)
Mining Industry Similarity	-0.802*** (0.123)	-0.674*** (0.155)	-0.719*** (0.091)
Distance between most populous cities	-0.139*** (0.015)	-0.027** (0.013)	-0.084*** (0.010)
Population of territory i	0.107*** (0.018)	0.044* (0.026)	0.097*** (0.015)
Population of territory j	0.0489*** (0.0144)	0.104*** (0.019)	0.084*** (0.011)
Border	-0.205*** (0.0474)	-0.184*** (0.054)	-0.314*** (0.042)
International exports/GSP for territory i	N/A	1.081*** (0.414)	N/A
International exports/GSP for territory j	N/A	-0.118 (0.143)	N/A
NAFTA	N/A	N/A	-0.241*** (0.013)
NAFTA * Border	N/A	N/A	0.177*** (0.049)
Intercept	0.976*** (0.1074)	-0.056 (0.140)	0.492*** (0.091)
Adjusted R^2	0.296	0.161	0.236
Standard error of regression	0.297	0.330	0.320
F-test p-value	0.00	0.00	0.00
Durbin-Watson statistic	1.434	1.617	1.524
White test with cross terms LM statistic	293.402	204.842	406.665
White test p-value	0.00	0.00	0.00
White test F statistic	10.081	4.224	9.404

Table 2. Regression results for the pre-NAFTA, post-NAFTA and panel data models, with Newey-West standard errors. 1, 2, or 3 stars next to the estimate represent statistical significance at the 10%, 5%, and 1% level, respectively.

For the pre-NAFTA sample regression function, all parameters are statistically significant at the 10% level, and all but manufacturing are statistically significant at the 1% level. All parameter estimates, minus manufacturing, take signs consistent with a priori expectations. The model explains a statistically significant portion of the variation in GSP correlation, with variation in the regressors explaining approximately 30% of the variation in GSP growth correlation. The Durbin-Watson statistic for the pre-NAFTA OLS estimates is calculated at 1.434. At n = 1,830 and with 8 regressors, we reject the null of no autocorrelation in the residual term, indicating that the residuals may follow an AR(1) process. The White test with cross terms confirms the presence of heteroskedasticity in the residual terms. The LM statistic equals 293.402, well past the critical value necessary to confirm unequal error variance. Since these tests show that heteroskedasticity and autocorrelation are present with conventional standard errors, the Newey-West standard errors resolve this issue.

The empirical results for the regression model following NAFTA implementation change drastically relative to the pre-NAFTA estimates. The sample regression function explains a statistically significant portion of the variation in GSP growth correlation at the 1% level, with variation in the regressors accounting for approximately 16.1% of the variation in GSP growth correlation. The adjusted R^2 of this model is considerably less than the 0.30 adjusted R^2 for the pre-NAFTA regression. The post-NAFTA regression's Durbin-Watson test produces a d-statistic of 1.617. As before, the presence of an AR(1) process in the residual term is suggested, justifying use of the Newey-West HAC covariance matrix. Inequality in the residual terms again seems likely, as the LG test value is 204.842, well past the critical value necessary to confirm heteroskedasticity in the original OLS residuals. The pooled model explains approximately 23% of the variation in GSP pair-wise correlation, and its Durbin-Watson and White test results again confirm the necessity of using Newey-West standard errors in the panel data regression.

Agricultural sector similarity is the strongest trade determinant of pre-NAFTA cycle correlation, with a 1% difference in the agriculture share of GSP between two territories weakening predicted cycle correlation by 1.55%. In the post-NAFTA regression, agriculture industry similarity weakens as a strong determinant of correlation, with the parameter estimate decreasing from -1.546 to -0.849. The estimate remains statistically significant at the 5% level. Agriculture structure similarity remains the strongest determinant of business cycle correlation in the panel model as well, with a parameter estimate of

-1.163. This estimate has a smaller magnitude than the pre-NAFTA estimate, but remains larger than the post-NAFTA estimate.

Prior to NAFTA, mining industry similarity has a sizable effect on cycle correlation, with a 1% increase in mining sector dissimilarity lowering predicted growth correlation by 0.8%. Mining similarity weakens as a determinant of correlation after NAFTA ratification, with the parameter estimate shifting from -0.802 to -0.675, but remains statistically significant at the 1% level. The panel data model's mining similarity parameter estimate increases to -0.720, compared to the post-NAFTA model's estimate of -0.675.

Based solely on the pre- and post-NAFTA regression models, following NAFTA ratification, industry structure similarities in agriculture and mining weakened as determinants of state and provincial business cycle correlation. Additionally, manufacturing became a statistically significant determinant of cycle correlation in the post-NAFTA era. One possible explanation for the reduction in agriculture and mining similarity's effects on business cycle correlation is that with increased economic integration between the US and Canada in the form of reduced trade barriers and tariffs, the transmission of industry-specific shocks was muted. Integration of goods and asset markets may create a more effective shock transmission mechanism, allowing a more complete dispersal of industry-specific shocks throughout all state-level economies, regardless of the level of industry structure similarity. Therefore, differences in agricultural and mining industry structure may not impact GSP growth correlation as strongly.

Manufacturing similarity has a statistically significant and synchronizing effect on states' growth correlation. A 1% increase in the difference between manufacturing as share of two states' GSP increases the predicted value of growth correlation by 0.12%. After NAFTA ratification, the parameter estimate on manufacturing takes the expected negative sign, and becomes strongly negative, with a 1% increase in manufacturing sector dissimilarity weakening predicted synchronization by 0.9%. The manufacturing variable's parameter estimate decreases drastically from -0.990 in the post-NAFTA regression, to a statistically insignificant -0.093 in the panel data model. The small magnitude of the pre-NAFTA and panel estimates may indicate substantial market segmentation in manufactures trade prior to NAFTA, if dissimilarity in this sector only weakly impacts cycle synchronization.

NAFTA's elimination of tariffs on motor vehicles, electronic products, and textiles led to an appreciable increase in intra-manufacturing trade between 1994 and 2004. As the US and Canada witnessed a huge increase in trade volume in these outputs, it is reasonable to argue that the once-segmented manufacturing sector became highly integrated, with substantial differences in manufacturing industry structure now strongly impacting GSP growth correlation. This would explain the shift in statistical significance and parameter signage in the pre- and post-NAFTA model, as well as the negative parameter estimate in the panel model.

Distance between the most populous cities has the expected substantial effect on correlation, with a 1% increase in distance between largest cities by territory weakening predicted correlation by 14%. Post NAFTA, the coefficient estimate on the distance variable decreases in magnitude, shifting upwards to -0.027. Following NAFTA ratification, physical distance between territories within the US and Canada weakens substantially as a desynchronizer of business cycle correlation. In the panel data model, the distance variable remains a strong determinant of cycle correlation, with a coefficient estimate of -0.084 significant at the 1% level. With the technology boom of the 1990s, advances in telecommunications and transportation technologies enabled cheaper and faster transportation of tradable commodities, perhaps weakening distance's effect on business cycle correlation.

Prior to NAFTA ratification, both population variables are statistically significant and positive at the 1% level as determinants of GSP growth correlation. After 1993, the population parameters shift in value considerably. The coefficient estimate on the population of territory *I* remains positive, but decreases from 0.107 to 0.044, and is now statistically significant only at the 10% level. Territory *J*'s population strengthens as a determinant of business cycle correlation, increasing to 0.104, and remains statistically significant at the 1% level. Within the pooled regression, the two population variables' coefficient estimates are statistically significant at the 1% level, with correct signage and estimates close in value to those of the post-NAFTA estimates. Additionally, their coefficient values lie within .01 units of each other, unlike the previous regressions' distance variables' coefficients.

The post-NAFTA export variables produce contrasting results. Exports as a share of GSP for state *I* were a statistically significant determinant of business cycle correlation at the 1% level, with a 1% increase in exports as a share of state *I*'s GSP increasing cycle correlation by 1.1%. However, exports as a share of GSP for territory *J* was statistically insignificant at and beyond the 10% level. The coefficient on this variable was -0.118, indicating that for a 1% increase in exports as a share of territory *J*'s GSP, business cycle correlation between the two territories weakens by 0.12%. These estimates imply that a state's own exports as a share of GSP is more important in terms of its pair-wise synchronization with other territories, relative to other territories' exports as a share of GSP.

The pre-NAFTA border has a statistically significant and strong desynchronizing effect on state and provincial level cycle correlation. The border weakens the estimated value of pair-wise business cycle correlation by 20.5% in the pre-NAFTA time period. The border dummy remains statistically significant at the 1% level in the post-NAFTA segment, and decreases in negativity to -0.18. Following NAFTA ratification, the geographical border weakens slightly in its capacity as a state-level desynchronizer. The panel model's border coefficient is the largest of all three border estimates. All regressors held constant, the correlation of GDP growth between a province and a state is 31.4% weaker than the correlation of GDP growth between two provinces or two states. The negative parameter estimate on the NAFTA dummy indicates that post-NAFTA, GSP growth correlation between all territory pairings, intra- and international, decreases by 24.1%. Contrary to established literature, this analysis argues that NAFTA had a significantly disaggregating effect on regional economies.

Interacting the border dummy with the NAFTA dummy produces a term with a coefficient estimate of 0.177, statistically significant at the 1% level. Multivariate calculus reveals how this interaction term affects the economic interpretation of the border and NAFTA dummies. The partial derivative of the sample regression function with respect to the border is:

$$\boldsymbol{\delta \rho_{i,J} / \delta \, \text{Border}_{i,J} = -0.314 + (\text{NAFTA} * 0.177)}$$

Prior to NAFTA ratification, the correlation of GSP growth between a province and a state is weakened by 31.4%, relative to an intra-national territory pair. After NAFTA ratification, state-province GSP growth correlation weakens by only 13.7%. NAFTA ratification mitigates the desynchronizing force of the geographic border to some extent.

The partial derivative of the SRF with respect to NAFTA is:

$$\boldsymbol{\delta \rho_{i,J} / \delta \, \text{NAFTA}_{i,J} = -0.241 + (0.177 * \text{Border})}$$

NAFTA weakens intra-national pairs' GSP growth correlation by 24.1%. For state-province pairs, NAFTA weakens GSP growth correlation by only 6.4%. While NAFTA had a highly desynchronizing effect on intra-national pairs, its effect is much weaker on state-province pairs. One valid argument against this analysis is the question of whether a similarly important economic event in the 1990s strongly impacted US-Canada goods trade, and the NAFTA and border dummies are simply absorbing that event's effects into their estimates. While the possibility exists that other events occurring from 1984 to 2004 impacted pair-wise GSP growth correlation, the likelihood is that inter-territorial trade is the main explanatory variable influencing pair-wise GSP growth correlation. The scatter-grams on the following page corroborate this assertion. Within these graphs, we clearly see a positive relationship between exports as a share of GSP and business cycle correlation.

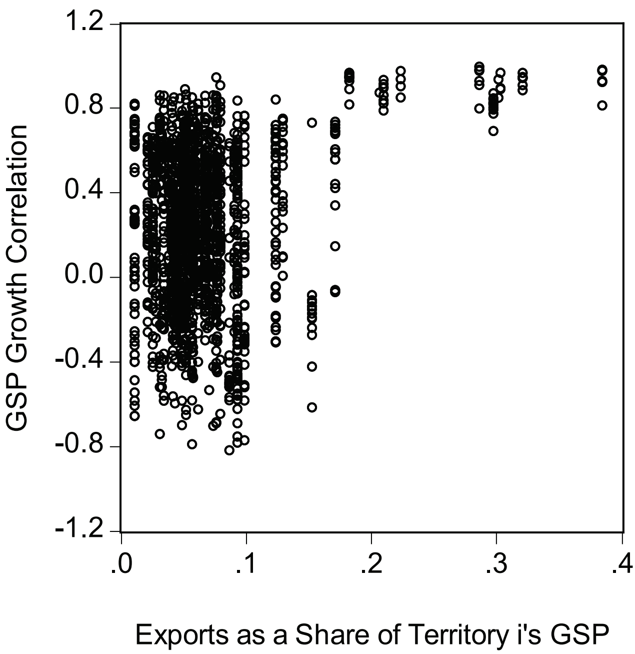

Figure 1. Scatter-plot of exports as a share of state *I*'s GSP in relation to GSP growth correlation. Note the positive trend in the scatter-plot.

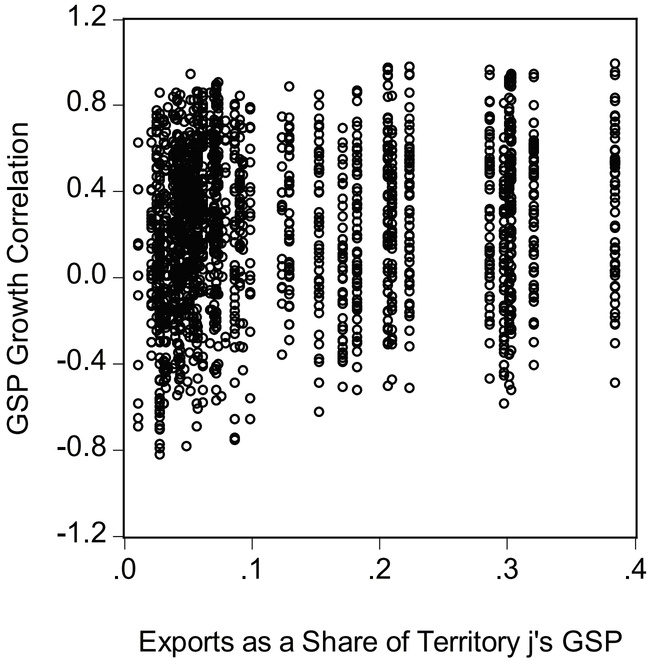

Figure 2. Scatter-plot of exports as a share of territory *J*'s GSP in relation to GSP growth correlation. Here the trend is less clear, but there remains a positive trend between the two variables.

Conclusions

The border reduces cross-border pairs' GSP growth correlation by anywhere from 18% to 31%. Despite substantial trade integration, state and province pairs' GSP growth remains strongly desynchronized. Disparities in taxation and trade regulations may remain, functioning as a disincentive for trans-border goods trade. Home market bias may also influence US and Canadian firms' decisions to trade. The border's geographic and legal effects remain an obstacle to business cycle synchronization. Yet in relation to NAFTA, the border had a synchronizing effect. Via partial derivative analysis, the border increases the predicted level of cross-border pairs' GSP growth correlation, reducing NAFTA's strongly desynchronizing effects. With the elimination of virtually all economic barriers to cross-border trade, it is reasonable to conclude that the doubling of goods trade between states and provinces over a ten-year period reduced NAFTA's impact on business cycle correlation between states and provinces. GSP growth correlation between cross-border pairs weakens by 31.4%, prior to NAFTA ratification. Post-NAFTA, GSP growth correlation between cross-border pairs weakens by only 13.7%. While NAFTA may have desynchronized intra-national pairs, its effect is much weaker in international pairings.

In the panel data regression, NAFTA alone was found to desynchronize territory pairings by 24.1%. In a vacuum, this might be used as evidence to argue the notion that free trade agreements are inherently desynchronizing. The trade agreement may have had a desynchronizing effect by inducing states and provinces to specialize in specific industries, per the Ricardian theory of comparative advantage. With different territories specializing in different industries, industry-specific shocks would no longer produce symmetrical responses within state-level economies. It appears that NAFTA's primary effect was to generate simultaneous business cycle desynchronization between state-province pairs, state-state pairs, and province-province pairs. Though NAFTA had the synchronizing effect of integrating multiple sectors of the goods market of both nations, its desynchronizing effect also decoupled domestic economies from within. NAFTA was ratified at the same time the border's relevance as a desynchronizing force was reduced, due to tariffs and trade barriers, coupled with advances in transportation and telecommunications technology. These two events opened up new markets for states and provinces with economies centered on industries producing tradable output. As a consequence of the Ricardian law of comparative advantage, states found themselves trading more with provinces whose economic structures matched their own, and thus the desynchronizing effects of NAFTA were reduced to some effect, although not completely negated. This reinforces the notion that business cycle shocks are industry driven, as opposed to demand driven.

One theory to explain the mechanisms of the post-NAFTA environment is the following: NAFTA ratification lowered barriers to increased goods trade, inducing territories to specialize in differing industries. As a result, the NAFTA induced desynchronization between territory pairs. However, those states specializing in identical industries witnessed such an increase in intra-industrial trade that a net synchronization was created in those pairs. Cycles may be becoming more industry-driven, and what is being witnessed post-NAFTA is the generation of industry cycles that territories are tied to. This theory accounts for the regression results and the positive trend between exports as a share of GSP and business cycle synchronization. At an aggregate level, NAFTA can desynchronize pairs by spurring trade specialization, but also induce trade creation that creates industry-driven business cycle synchronization, partially negating the decoupling. Post-NAFTA, GSP growth correlation both intra-nationally and internationally has decoupled. Further empirical work is forthcoming. Gravity model variables will be added, including transportation expenditures as a share of two territories' combined gross product. With this, we can determine the effect transportation technology has on synchronizing economic growth. More sectors of the economy producing tradable output will be also be considered.

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The Genetic, Social, & Behavioral Factors That Motivate Parents to Abuse their Children

Brad Garner

Introduction

This paper examines the influence of economic, genetic, behavioral, and social factors on the parental choice to abuse one's child. I derive a choice model for the parents based on McFadden's (1974) conditional logit model. Within society, the parent or parents not only bear the responsibility for their child's well being, but also for ensuring the child will grow up to be an educated, productive member of society. Through the examination of individual parent and child behavior patterns, as well as numerous social and economic factors from the Physical Violence in American Families Survey of 1985, I show that after a child behaves in a certain manner, the parent chooses to abuse based on numerous social, economic, and genetic variables. Child abuse is a social problem that has not been examined heavily in the field of economics, but with the help of econometric analysis I examine how behavior and social trends can increase the probability of child abuse. Hopefully this analysis will lead to suggestions on how to remedy this problem.

In the next section I show how other studies have approached similar problem and their findings. After the presentation of the literature I explain my parental choice model and what factors influence this model. Following the presentation of the model I discuss the data from the survey and what variables were used and how they have been modified. I then use the data to support my theory and conclude with a discussion about what factors influence the parental choice to abuse.

Literature

Several scholars examine poverty and family economic status to see if income level is a deciding factor in child abuse. These studies argue that lower income levels increase parental stress level (as parents have a harder time making ends meet), thus making parents more likely to use abuse (Berger 2004, 725-748; Drake and Pandey 1996, 1003-1018; Egeland 1979, 269; Gil 1970; Iverson and Segal 1990; Medora, Wilson, and Larson 2001, 335-348; Straus 1979, 213). This is also confirmed by numerous studies which find that the presence of neglect is also highly influenced by poverty (Finkelhor and Jones 2006, 685-716; Paxson and Waldfogel 2003, 85-113). One can see that this is a logical argument as poverty can lead to a higher parent stress level. Higher stress levels may lead to loss in self-control, resulting in abuse (Herrenkohl, Herrenkohl, and Egolf 1983, 424-431). My study examines multiple income levels in order to see which ones are more prone to abuse.

Abuse history is another factor that is found to increase the risk that this parent uses violence with their own children (Gil 1970; Iverson and Segal 1990; Straus 1979, 213). Other parental characteristics found to influence abuse are: age, gender, family structure, education, ethnicity, and family structure (Gil 1970). Substance abuse is another key factor that may increase the probability of abuse occurring (Gil 1970; Markowitz and Grossman 1998). Parental expectations for the child as well as parental understanding (or misunderstanding) of child behavior are factors parents do control.

A child may behave in a certain manner, regardless of intent, and this act or actions may be interpreted by the parent as negative behavior (Gil 1970; Herrenkohl, Herrenkohl, and Egolf 1983, 424-431; de Lissovoy, Vladimir, Dr. 1979, 341). Parent reaction can be determined by numerous traits such as those discussed earlier, but also variables such as personality which can not be quantified accurately. Thus, the child's behavior must also be considered in the pool of variables that determine abuse (Lynch 1976, 43).

Mammen et al. (2003) examines how parental cognitions and satisfaction[1] lead to child abuse. This study hypothesizes that parental expectations for the child, inability to control parenting situations, and "hostile attribution bias" (parents perceiving innocent child behavior as intentionally hostile) would all lead to increased parental frustration and in turn child abuse (Mammen, Kolko, and Pilkonis 2003, 288). The examination finds that none of these factors contributed to aggressive parent behavior, suggesting that child maltreatment is rather derived from parental satisfaction with the child (Mammen, Kolko, and Pilkonis 2003, 288). This study suggests an interesting point about the degree of abuse that is used. If a parent is more or less satisfied with their child, they may be more likely to use higher levels of violence (dissatisfied), or lower levels of violence (more satisfied), assuming the parent abuses. Egeland (1979), presents the contradictory argument that inadequate mothers do not understand their own children or the process of child development. If a mother

1 Parental cognitions considered by the study are unrealistic expectations for the child by the parent, if the parent feels they have a lack of power in care giving situations (thus making them feel "threatened"), and if the parent interprets innocent child behavior as malicious. Satisfaction refers to how satisfied the parent is with the child.

does not understand their own child, how can they understand the reasoning behind a certain behavior?

In his construction of an equilibrium model for child development, Akabayashi notes that parents may have lofty expectations for their children and that the children may never live up to these expectations. The parents are then forced to relieve their frustrations through abuse (Akabayashi 2006, 993-1025). The construction of this model takes into account the child's human capital, the effort of the child, and the parenting strategy, all of which lead to a relationship where the parent provides services to develop the human capital of the child (Akabayashi 2006, 993-1025). Also taken into account is the amount of time the parent spends with the child, which can lead to a more accurate perception of child behavior, lessening parental frustration when a child behaves a certain way (Akabayashi 2006, 993-1025). Agee, Crocker, & Shogen present a similar model where abuse is a result of a loss of self control or loss of self composure by the parent (Agee, Crocker, and Shogren 2004, 1-39).

The status (adopted, foster, etc.) of the child is another factor that should, but does not seem to increase the probability of child abuse (Gelles and Harrop, 1991). This study found, using empirical analysis of the National Family Violence Survey, that non-genetic children were actually abused less than genetic children (Gelles and Harrop, 1991). It is also interesting to point out that abortion has led to a decline in child abuse rates. Assuming biological children who are unwanted are more likely to be abused; abortion eliminates this problem (M. P. Bitler & Zavodny, 2004; M. P. Bitler & Zavodny, 2002).

From the reviewed works it seems that there is a combination of factors, rather than individual factors, leading to abuse. (Gil 1970; Straus 1979, 213). Parental frustration with the child and the parents stress level are two factors that should increase the probability of abuse. Each individual parent has a different breaking point. Some parents snap under low levels of frustration or stress and some parents are more patient. My study shows there is not only a wide combination of factors, but that child behavior is the inciting factor for the use of abuse. The literature reviewed demonstrates that numerous environmental and genetic factors may come into play, but few demonstrate the importance of behavior empirically. The studies presented here also emphasize that the decision to abuse falls on the parent who is subject to numerous social and genetic constraints. My study not only examines more environmental and genetic factors, but also argues that the constraints on the parent influence the decision to abuse when the child behaves a certain way. Unlike any other study I also present a parental choice structure for the parent to abuse.

Theory

Again, my question is: Given the presence of certain types of child behaviors, what parental factors determine whether or not a parent will abuse their child? My hypothesis is that certain factors exist; genetically, socially, and behaviorally, for a given parent and a given child that increase the probability of abuse. A key part of this argument is parental utility and the factors that determine it. This is important as it allows me to present child abuse as a derivation of McFadden's conditional choice model. The utility of parent *p* (u_p) is determined by not only by child utility (u_c), but also by the child's well being (*CWB*), thus:

$$u_p = f(u_c, CWB) \qquad (1)$$

Child utility is determined by the child's happiness, as a child is happiness translates to parental happiness (Akabayashi 2006, 993-1025). Child well being is defined as the action by the parent which is in the best interest of the child. An example of this is child vaccinations. Children may hate getting inoculated for diseases such as polio, but it is necessary to prevent the child from contracting this disease. I assume that children, especially the younger ones, do not completely comprehend the difference between good and bad behavior, as some children may find bad behavior utility maximizing. Assuming this argument is true, parents can not always allow their children to maximize their utility as it may be detrimental to the child as well as others. Abuse is assumed to be detrimental to the child both in utility and in well being, thus it is also detrimental to overall parental utility (Agee, Crocker, and Shogren 2004, 1-39).

Further, each parent faces a discrete choice, to abuse (*a*) or not to abuse (*na*), and selects the choice that maximizes utility (Manski 2001, 217). Assuming that the parents behave rationally they make the choice not to abuse:

$$u_p(na) \geq u_p(a) \qquad (2)$$

But because child abuse does occur, some parents are not acting completely rationally:

$$P(a) = P[p : u_p(a) \geq u_p(na)] \qquad (3)$$

This is the probability that parent *p* has the utility function where abuse is the optimal choice (Manski 2001, 217).

Considering these assumptions, I now present the following decision tree to illustrate the choice structure of the parent (Figure 1). Child behavior is the first node on the decision tree. The child has two choices, good and bad behavior. The behavior classification is determined by the parent, due to the assumption previously mentioned about some children not knowing the difference between good and bad behaviors. In reality there are shades of gray with child behavior, but for this purpose I assume the parent sees it either as good or bad. The parent must then decide how to act based on their interpretation of the child's actions. The parent has three choices: no response, abuse, or other response (i.e. praise, or other punishment). Before I continue I need to note that much of this decision is determined by parental perception. The parent may see a child's behavior as malicious, but when in reality the child meant no harm (Mammen, Kolko, and Pilkonis 2003, 288).

The parent's decision (*PD*) of what reaction to use, given the presence of a certain type of child behavior (*B*), is defined by the function:

$$(PD \mid B) = f(PP, PE, PG, PA, CA, CG, PAH, PAU, PR, PI, PES, FS, PPL, PPS, CI, N) \tag{4}$$

Where PP is parental personality, PE is parental expectations, PG is parent gender, PA is parent age, CG and CA are the gender of age of the child respectively, PAH is the parent's abuse history, PAU is the parent's alcohol use, PR is the race of the parent, PI is parental income level, PES is the parent's emotional status, FS is the family structure, PPL is parental problems with the law, PPS is the pregnancy status of the female parent, CI is the intentions of the child from the parent's perspective, and N is a variable representing other factors in the parent's life that are determined by nature. This can be expressed in terms of McFadden's conditional logit model.

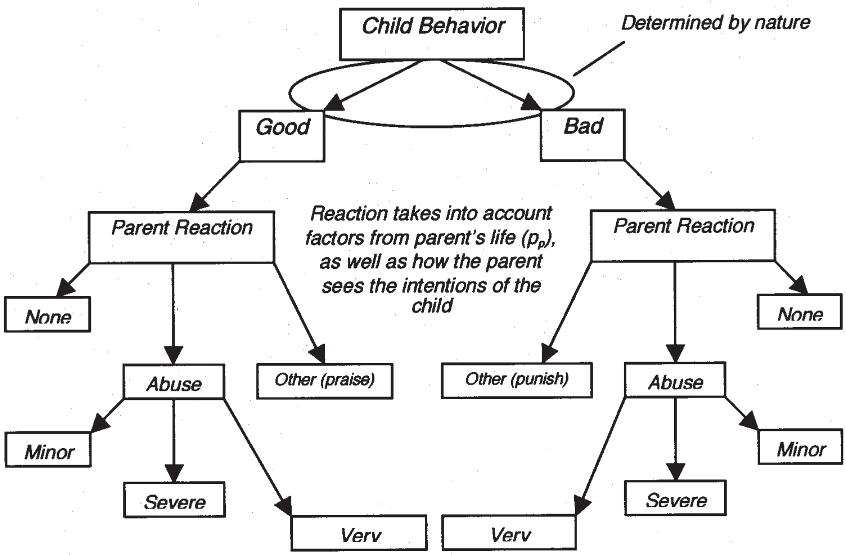

Figure 1

Before I present my choice model with this I must note that while McFadden's rational choice model may not make sense in this context as abuse is not a rational choice, the basis of this model makes the most sense in this context. Abuse is not always a choice parent's consciously make, instincts and other factors come into play. While this may hold true for the majority of cases; I am attempting to show that when parents choose to abuse there are factors that make the parent choose abuse, even if the choice is sub-conscious. The following utility functions serve as the foundation for McFadden's conditional logit model and are derived from Manski (2001), Maddala (1983), and McFadden (1974, 1980).

$$u_p(a) = u(c_a, p_p) \qquad (5)$$

Equation 5 shows the utility for parent p ($u_p(a)$) when this parent chooses to abuse their child can be expressed in terms of a vector of attributes which characterize the child who is abused (c_a), and a vector which classifies the characteristics of the individual parent (p_p) (Manski 2001, 217). However one can only use observed values, thus the equation becomes:

$$u(c_a, p_p) = v(c_{ao}, p_{po})\beta + \varepsilon_{pa} \qquad (6)$$

where c_{ao} and p_{po} represent the observed vectors for the abused child and parent who chooses abuse respectively. In Equation 6 the error expresses any unobserved attributes to utility (Manski 2001, 217).

Equation 6 can be transformed into a conditional choice probability model:

$$P(noabuse \mid p_{po}, A_o) = P(v(c_{nao}, p_{po})\beta + \varepsilon_{na} \geq v(c_{ao}, p_{po})\beta + \varepsilon_a \qquad (7)$$

Where A_o is the observed attributes of the abused child, including behavior. This model shows the probability of parent *p* selecting the choice not to abuse, given a set of child characteristics (Manski 2001, 217). Equation 7 leads to the conditional logit model:

Y^*_{pa} = The level of indirect utility if a given parent chooses to abuse
$Y_{pa} = 1$ If the parent chooses to abuse
$Y_{pa} = 0$ otherwise
Using the previous equation I further assume:

$$Y^*_{pa} = \beta(c_a) + \alpha_a(p_p) + \varepsilon_{ana}$$

Thus this becomes:

$$P_{pa} = \mathrm{Prob}(Y_{pa} = 1 \mid B) = \frac{e^{\beta(c_a)+\alpha_a(p_p)}}{\sum_{k=1}^{3} e^{\beta(c_a)+\alpha_a(p_p)}}$$

(Maddala 1983; McFadden 1974, 1980) *(8)*

This equation is derived by McFadden and shows the probability that parent p with attributes *p*, makes the choice to abuse given the child with attributes *c* exhibits a certain behavior (*B*). From this conditional choice model I show that when the parent decides to abuse, the decision is determined by a set of parent and child characteristics. These characteristics should be present in parents who consciously choose to abuse, and parents who "lose control" and do not consciously choose to abuse their children. I also show the importance utility plays in this model. Again, regardless of whether the parent consciously makes the choice to abuse, parental utility from abuse is determined after the abuse occurs.

Child behavior is the condition for this model. I believe the probability of abuse increases when a child exhibits a negative behavior. Due to restrictions in the data I am only to take into account three behaviors that have the good/

bad distinction. It is important to note that the decision of how to react to child behavior occurs only at time t, even though some of the variables which affect this decision are determined at an earlier time. The three variables are: if the child has a temper tantrum, if the child has disciplinary problems at school, and if the child is failing school. Temper tantrums are defined by the National Library of Medicine as "disruptive or undesirable behaviors or emotional outbursts displayed in response to unmet needs or desires. [Temper tantrums] may also refer to an inability to control emotions due to frustration or difficulty expressing a particular need or desire" (Medline Plus 2008, 2). The definitions of the other behavior variables are self explanatory. If the child has temper tantrums or disciplinary problems at home it should signal good or bad behavior, and also suggest if the presence of a certain behavior increases the probability of abuse. The failing school variable tests if parental expectations do factor into the use abuse. Summary statistics and cross tabulations for these variables can be found in Appendix A. In order to determine how these behaviors impact the explanatory variables, interaction terms were created.

Referring back to Figure 1, the parent's decision has three outcomes depending on the behavior. They are: no response, some other response (i.e. praise or form of punishment that is not abuse), or abuse. If the parent chooses abuse, they select from three forms: minor, severe or very severe. These are defined as follows (Straus and Gelles 1990):

- Minor violence- threw something at another family member, pushed, grabbed, shoved, or spanked.
- Severe Violence- kicked, bit, punched, hit or tried to hit with object, beat up, choked, burned, scalded, threatened with a knife or gun, used knife or gun.
- Very Severe Violence- Created to account for actions other than hitting a child with an object (i.e. a belt) which is sometimes considered part of traditional punishment

This decision is defined by a similar equation as the initial parental decision (Eq. 4), only it now determines the type of violence on the condition that the parent chooses to abuse.

Based on the assumptions of my model, parent's do not want to abuse their children as it is detrimental to both the parent and the child in terms of utility and child well being. In the decision tree, the choice to abuse is the least optimal given a certain child behavior. "No Response" is not the optimal choice either as it does not reinforce good behaviors, or attempt to correct bad behaviors. Other is the optimal choice as it encourages good behavior through praise, and corrects bad behavior through an optimal form of punishment. However, as noted earlier many parents do not consciously make the choice to abuse. This is where my theory about parents choosing to abuse based on utility breaks down. While theory can not perfectly predict parental behavior, my results show what characteristics modify the probability of abuse. I propose that children, who are exposed to abuse, not only behave a certain way, but also are raised by parents which have certain markers for child abuse.

In order to do this I predict multiple regressions. First I use a logit model as my dependent variable is binary. The behavior interaction terms demonstrate how certain independent variables change the probability of abuse, when the behaviors are present. Summary statistics for the interaction terms that are statistically significant from the non-interaction terms are in Appendix A. The first set of predictions include my independent variables as well as the significant interaction terms. I also present odds-ratios with this prediction. Odds ratios are interpreted as difference from one, and show how the variables affect the odds of abuse being present. After determining what factors affect the probability a given parent chooses to abuse, I predict a second logit model, ordinal in nature, to determine what type of violence the parent will use (summary statistics in Appendix A). I use an ordered logit as my dependent variable is ordinal in nature and it allows me to predict what characteristics, including the behavior interaction terms, increase the likelihood of a parent choosing a certain type of violence. The results of these predictions show what characteristics increase the likelihood of a parent using a higher level of violence. The cut-values demonstrate where the dependent variables are divided for each level of violence. I now discuss my initial expectations for the independent variables which are derived from reviewed literature as well as cross-tabulations

I expect the gender of the respondent variable to be positive, signaling that females are be more likely to abuse. This is grounded in the idea that females spend more time taking care of children, creating more opportunities to abuse than males. I predict the age of the respondent to be negative, as younger parents are less experienced and turn to abuse as a disciplinary solution than more experienced parents. I expect child age to be negative, as younger children are more likely to be abused as they require more care from the parent as increased needs may cause parental frustration, thus leading to abuse. The cross-tabulations show that as child age increases the number of abuse cases decreases. This also may be due to the fact older children can defend themselves more effectively. Parent age and child age are somewhat correlated as younger parents most likely have younger children. I expect child gender to be negative, signaling male children are more likely to be abused, as male children are more prone to bad behavior. The behavior interaction term is not significant from the non-interacted gender variable. This demonstrates that behavior is a factor in the non-interacted term, asserting my initial expectation.

I so not expect parents who were exposed to domestic violence as a child to be more likely to abuse. I think domestic violence breeds more domestic violence, not more child abuse. If the respondent was abused by either of their parents when they were children, I expect the respondent to be more likely to use abuse. This is derived from the idea that abuse lead to more abuse. If the respondent has been arrested in the previous year there are two possibilities: the parent is in jail, away from the child, and unable to abuse; or because the parent has broken the law, they may be more violent than other parents. A former convict as a parent may also have missed a significant portion of a child's life and this could increase parental frustration. There are two possibilities with alcohol consumption: parents either become more violent under the influence or more tolerant depending on the manner in which alcohol affects them. The cross-tabulations show that there are more cases of abuse than non-abuse as the number of drinks per day increases.

Asserting the beliefs of the literature I believe that parents who feel stressed, depressed, or have thought about suicide are more likely to abuse as stress is a factor that may cause parents to snap, leading to more abuse. I also have parallel expectations with the literature when it comes to income levels. I predict that lower income levels should increase the probability of abuse. For the race variables, I could argue minority races are more or less likely to abuse, but there is no plausible theory to support either argument. I think the results of the race estimates may be proxies for other variables that have not been included in this model, such as education level and employment status. If the respondent is pregnant I expect a higher probability of abuse, as pregnant women are assumed to be under more stress (physically and emotionally) than other parents and therefore be more likely to turn to abuse. Unlike the reviewed literature, if the family is a step or single parent family, I expect to see a positive relationship. I expect this with step families because one parent is not biological and may be more likely to abuse a child that is not theirs. Single parent families typically struggle to make ends meet; therefore, my reasoning for this is similar to my argument for income level. Finally, with the child behavior interaction terms, I expect these to show that parents with certain characteristics to be more likely to abuse their child given the presence of a certain child behavior.

Data

The ideal data for a study such as this would be statistics about every case of child abuse and the environments in which each case occurred. While this data is over twenty years old, I do not feel this makes a difference. Unfortunately, some variables that may make a parent use abuse, such as emotion, are not easily quantified. I believe that the genetic and demographic variables that contribute to abuse have not changed significantly over time. Since child abuse is an illegal activity, data only exists about reported cases, I examine those cases to see if there are any consistencies among cases.

The data come from the 1985 Physical Violence in American Families Survey. This survey was a follow up to a similar survey done in 1976. "The main component of this survey design was a national cross-sectional survey of adults in the United States who either (1) were currently married or living together, (2) were single parents with children under 18 in the household, or (3) had been married or had lived with a partner of the opposite sex within the past two years" (Codebook). The dependent variables are considered Conflict Tactics Scale Violence Rate Variables which are divided into three types of violence, minor, severe, and very severe (Straus and Gelles 1990). These variables were manipulated to create a single variable, if abuse was present at all regardless of type, and a scale variable for the type of violence. The majority of the independent variables are dummy variables denoting either specific responses (i.e. 1=female and 0=male) or certain levels, such as income and the amount of drinks people consume. Again, more in depth data definitions are contained in Appendix A.

The data do present some limitations in my attempt to produce results. The survey has 6,002 observations. With the numerous manipulations of the data, some variables lack significant observations to be considered accurate. This is reflected in the dependent variables. Out of the people who answered the abuse questions, 60% said they abuse. This is possible, but I feel with more observations, this number might decline. Survey form also naturally draws into question the validity of the answers. People could easily give false answers and I see some examples of this present in the summary statistics. I find it highly unlikely someone can consume 40 drinks in one day. Thus, the results produced in this study must be interpreted with caution. This survey is one of the better sources of statistics that show the factors that contribute to child abuse. No other survey has the depth of possibly significant independent variables than this survey. It provides a more accurate picture when the independent and dependent variables are each from the same source.

From the summary statistics table in Appendix A I find the majority of the independent variables have upwards of the 6,002 observations. This is important as a relationship is established from the 3,338 observations for the dependent variables. The reasons for the significantly lower number of observations for the dependent variables is due to the fact there were numerous missing observations in the study. This occurs when the answer was "unknown" as opposed to "no" or "yes". It should be noted that numerous dummy variables were generated. The stressed, depressed, thought about suicide, income, race and family status variables all had to be converted into dummy variables for the different responses on the survey.

Results

The results for the initial model, determining what characteristics predict the probability abuse is present, is divided into three separate predictions. These results can be found in Table 1 (Standard errors in parenthesis, *denotes significance at 10% level, **denotes significance at 5% level, ***denotes significance at the 1% level, OR: odds ratio: maintains same significance as coefficient estimate)[2]. The first model (1) is my prediction with the temper tantrum (TT) interaction terms. The second model (2) is the prediction with the failing (FS) school interaction terms. Finally, the third model (3) is the model with the disciplinary problems (DP) at home interaction terms. The interactions terms demonstrate the effect of the given characteristic with the presence of the given behavior. The effect on the odds ratio is also reported. For interpretation purposes the closer the odds ratio is to 1, there is little or no change.

2 Note – both of the coefficient estimates for interactions terms for Hispanic and drinks per day were statistically significant in difference from zero at the 10% level. Both being Hispanic and consuming more drinks per day lowers the log-odds for abuse, holding constant the influence of other variables. These estimates are not very reliable, but are interesting especially the one concerning alcohol use, as it supports the idea parents may be more tolerant given a certain child behavior.

Table 4

	Interacted-TT (1)		*Interacted-FS (2)*		*Interacted-DP (3)*	
Variable	***Coefficient***	***Odds Ratio***	***Coefficient***	***Odds Ratio***	***Coefficient***	***Odds Ratio***
Gender: Respondent (Resp)	.4444*** (.12509)	1.56*** (.1951)	.4119*** (.1161)	1.509*** (.1753)	.3896*** (.1219)	1.476*** (.1799)
Resp Gender: Interaction	-.7951 (.5075)	.45155 (.2291)				
Resp Age	-.01937** (.0092)	.9808** (.0090)	-.01935** (.0088)	.9808** (.0087)	-.0199** (.0092)	.9802** (.009)
Resp Age: Interaction	.0452 (.0336)	1.0462 (.0351)	.0355* (.0288)	1.036* (.0299)	.03477 (.0402)	1.035 (.0416)
Child Age	-.093*** (.0132)	.9111*** (.0121)	-.0948*** (.0131)	.909*** (.0117)	-.0896*** (.0133)	.9143*** (.0122)
Child Age: Interaction					-.1789** (.0702)	.8361** (.0587)
Child Gender	-.363*** (.1064)	.6951*** (.07397)	-.3248*** (.1026)	.7226*** (.0741)	-.3463*** (.106)	.7073*** (.0749)
Resp: Father hit Mother	-.02716 (.17433)	.9732 (.1696)	-.1607 (.1663)	.8515 (.1416)	-.0462 (.1743)	.9547 (.1664)
Resp Mother hit Father	.1217 (.20689)	1.129 (.2336)	.3605 (.2091)	1.434 (.2998)	.1445 (.2055)	1.155 (.2375)
Resp Mother hit Father: Interaction			-1.192** (.6141)	.3035** (.1864)		
Resp Arrested in Last Year	.06394 (.4772)	1.066 (.497)	.1472 (.4425)	1.15 (.5127)	.1583 (.4592)	1.172 (.538)
Resp Drinks Per Day	.04471 (.0289)	1.045 (.0302)	.0446 (.0282)	1.045 (.0295)	.03813 (.0283)	1.0388 (.0294)
Drinks per Day: Interaction	-.2416* (.1481)	.785* (.1162)				
Resp Hit by Mother as Teen	.27038** (.1187)	1.31** (.1556)	.3182*** (.1143)	1.374*** (.1572)	.2552** (.1210)	1.291** (.1531)
Res: Hit by Father as Teen	.31359** (.1259)	1.3683** (.1723)	.2785** (.1248)	1.3212** (.165)	.3332*** (.1259)	1.395*** (.1757)
Resp Hit by Father: Interaction			1.329** (.4488)	3.778** (1.69)		
Resp Race: Black	.0184 (.1691)	1.018 (.1722)	.1286 (.1595)	1.137 (.1814)	.06877 (.1736)	1.071 (.1859)
Resp Race: Black: Interaction					-1.119* (.6739)	.3264* (.2199)
Resp Race: Hispanic	-.2172 (.1807)	.804 (.1454)	-.2208 (.1676)	.8018 (.1343)	-.3208* (.1744)	.7255* (.1265)
Hispanic: Interaction	-1.0525* (.5809)	.3490* (.2027)				
Resp Race: Other	.1274 (.2647)	1.135 (.3007)	.1826 (.255)	1.2 (.3063)	.1236 (.2627)	1.131 (.2973)
Income, $0 to $10,000	-.2513 (.2314)	.7774 (.18)	-.1246 (.2126)	.8827 (.1876)	-.1305 (.2247)	.8775 (.1972)
Income to $10,000 Interaction	2.19** (1.1234)	8.937** (10.04)				
Income, $10,000 to $20,000	.10162 (.1712)	1.069 (.1895	.0497 (.1667)	1.051 (.1752)	.0632 (.1723)	1.065 (.1835)
Income, $20,000 to $30,000	-.0265 (.1569)	.9738 (.15283)	-.0484 (.1535)	.9526 (.1463)	-.0234 (.1561)	.9768 (.1525)
Income, $40,000 to $50,00	.04938 (.1959)	1.051 (.2058)	.0037 (.1918)	1.003 (.1925)	.0129 (.1958)	1.013 (.1983)
Income, $50,000 +	.03793 (.1806)	1.038 (.1842)	.0563 (.1804)	1.057 (.1909)	.05811 (.1799)	1.059 (.1907)
Income $50,000+ Interaction			-1.362* (.771)	.2561* (.1974)		

Resp Stressed			-.0638 (.1702)	1.065 (.1814)	-.0254 (.1751)	1.025 (.1796)
Resp Stressed: Interaction			2.33** (1.228)	10.314** (12.672)		
Resp Depressed	.33833*** (.1313)	1.402*** (.1842)	.3466*** (.1373)	1.414*** (.1942)	.2877** (.1418)	1.333** (.1891)
Resp Thought about Suicide	.2430 (.2452)	1.275 (.3126)	.2118 (.2338)	1.253 (.289)	.2787 (.2426)	1.321 (.3205)
Woman Pregnant	.3833 (.3168)	1.467 (.464)			.4203 (.315)	1.522 (.4789)
Family Status: Step	-.0213 (.148)	.9789 (.1449)	.0410 (.1527)	1.042 (.1591)	-.0657 (.1479)	.9363 (.1385)
Family Status: Step: Interaction			-1.0389* (.5643)	.353* (.1996)		
Family Status: Single Parent	.2607 (.1893)	1.297 (.2457)	.2453 (.1611)	1.278 (.2059)	.3033* (.1927)	1.3544* (.2565)
Child: Temper Tantrum	.8204 (1.357)	2.27 (3.084)				
Child: Failing School			-3.646** (1.762)	.0261** (.0459)		
Child: Discipline Problems at Home					2.025 (1.403)	7.581 (10.642)
Constant	1.236*** (.362)		1.275*** (.3637)		1.294*** (.3755)	
Observations	1810		1930		1810	
LR-Stat	263.78 p:0.000		247.04 p: 0.000		252.96 p:0.000	
Pseudo R^2	.1110		.0977		.1064	
% Correct Predictions	72.49%		71.76%		71.99%	

These results provide some interesting answers to my initial hypothesis. All models are statistically significant, as can be seen from the LR-stat. Each model also has a Pseudo R^2 of about .1. Each model also predicts about 70% correctly. I find across the models there are some variables which consistently contribute to a change in the probability that a parent abuses. These variables are important as they signal that a parent's probability of abuse changes regardless of the presence of certain behaviors. All of the following estimates are statistically significant in difference from zero (most at the 1% level of significance), across all models, they are:

- Parent Gender (positive) - being female increases the log-odds of abuse by about .4, holding constant the influence of other independent variables. Being female also increase the odds of abuse by about .5. This is parallel with initial expectations.
- Parent Age (negative) - for each additional year of age, the log-odds of the parent using abuse decreases by about .019, holding constant the influence of other variables. As the parent gets older the odds of abuse decrease by .02 for each year. This is on par with a priori expectations that younger parents are more likely to abuse.

- Child Age (negative) – for each additional year of age, the log odds of the child being abused decreases by about .91, holding constant the influence of other variables. The odds-ratio decreases by about .09, for each additional year in age the child gains. This is also consistent with initial expectations that younger children are more likely to be exposed to abuse.
- Child Gender (negative) - being a female child, instead of a male, decreases the log-odds of abuse by about .092, holding constant the influence of other variables. If the child is female, the odds of abuse decrease by about .09. This agrees with initial expectations that males are more likely to be abused.
- Abuse History (positive) - if a parent was abused by their own parents as a teen (as opposed to not being abused), mother or father, the log-odds of abuse increases by about .3, holding constant the influence of other variables. If a parent was abused by their own parents, the odds of abuse increases by about .34. This is consistent with a-priori expectations.
- Depression (positive) - if the parent has ever felt depressed, as opposed to never feeling depressed, the log-odds of abuse increase by about .3383, holding constant the influence of other variables. If the parent is depressed the odds of abuse increase by about .4. This was my initial expectation as well.

These coefficient estimates for these variables demonstrate that there are certain factors outside of one's control that serve as markers for a parent to abuse. These results demonstrate that the biological and family history factors that influence a parent's choice to abuse no matter how the child behaves. I now present the statistically significant interaction terms from the first set of predictions.

I am only discussing the interaction estimates that are statistically significant in difference from zero at the 5% level of significance or better:

- Child Age (Discipline Problems Interaction) – In children who have disciplinary problems at home; each additional year in age decreases the log-odds of abuse by about .17, holding constant the influence of other variables. Also for each year older the child with disciplinary problems is, the odds of abuse decrease by .164. This is again consistent with initial expectations that younger children, especially those with disciplinary problems are more likely to be abused.
- Respondent's Mother hit their Father (Failing School Interaction) - If the parent's mother hit the parent's father and the child is failing

school, the log-odds of abuse decreases by 1.192, holding constant the influence of other variables. This may not be an accurate prediction, due to a small sample issue. There are only 28 observations where abuse was present and the respondent's mother hit the respondent's father.

- Abuse History (Hit by Father – Failing School interaction) - If a parent was abused by their father and the child is failing school, the log-odds of abuse increase by 1.329, holding constant the influence of other variables. Also if a parent was abused, and has a child failing school the odds of abuse increase by 2.778. These results are parallel with initial expectations and somewhat higher than the non-interacted term. This may reflect the parental expectations concept.
- Low Income ($0 to $10,000 – Temper Tantrum Interaction) – If the family does not make more than $10,000 and the child has a temper tantrum, the log odds of abuse increase by 2.19, holding constant the influence of other variables. If a parent makes less than $10,000 and has a child that acts out, the odds of abuse increase by 7.937. This is the only time any income estimate is statistically significant. I find that income is only a factor when the child misbehaves or annoys the parent, assuming temper tantrums are perceived in this way by the parent.
- Parent Stress Level (Failing School Interaction) – If a parent feels stressed and has a child failing school, the log-odds for abuse increase by 2.33, holding constant the influence of other variables. These conditions also increase the odds of abuse by 9.314. This is the only time the stress level of the parent was significant, showing that certain behaviors (i.e. failing to meet expectations) may trigger a parent to abuse when they are stressed.

From these significant interaction terms; I find that when a child behaves a certain way or fails to meet parental expectations, there are other factors (besides the previously discussed biological factors, which change the probability that a parent chooses to abuse. Now that I have shown what factors lead a parent to choose abuse, what factors influence the decision as to what type of violence to use?

The results of the interacted ordered logit models are presented in Table 2 (Standard errors in parenthesis, *denotes significance at 10% level, **denotes significance at 5% level, ***denotes significance at the 1% level). These models show what variables influence a parent's choice to use minor, severe, or very severe violence.

Table 5

Variable	*Interacted-TT*	*Interacted-FS*	*Interacted-DP*
Gender: Respondent (Resp)	.3684*** (.11355)	.3508*** (.1034)	.3467*** (.1079)
Resp Gender: Interaction	-.1621 (.31)		
Resp Age	-.0213*** (.0086)	-.0182** (.0082)	-.0177** (.0086)
Resp Age: Interaction	.071278*** (.0203)	.0456* (.027)	.03403 (.02633)
Child Age	-.0676*** (.01199)	-.0703*** (.0117)	-.07154*** (.0124)
Child Age: Interaction			-.00025 (.0388)
Child Gender	-.3595*** (.09388)	-.289*** (.0906)	-.3397*** (.0936)
Resp: Father hit Mother	.0270 (.15268)	-.1536 (.1468)	-.0038 (.1521)
Resp Mother hit Father	.1929 (.177)	.4404** (.1774)	.2313 (.1765)
Resp Mother hit Father: Interaction		-1.503*** (.5485)	
Resp Arrested in Last Year	.023707 (.3989)	.2031 (.392)	.2947 (.3984)
Resp Drinks Per Day	.0441* (.0253)	.0517* (.0243)	.0421* (.0246)
Drinks per Day: Interaction	-.00996 (.104)		
Resp Hit by Mother as Teen	.3371*** (.1044)	.3804*** (.1009)	.3396** (.1597)
Res: Hit by Father as Teen	.3407*** (.10995)	.2619*** (.1092)	.3451*** (.1122)
Resp Hit by Father: Interaction		1.504*** (.3774)	
Resp Race: Black	.3304** (.1519)	.3999** (.1469)	.3089* (.16377)
Resp Race: Black: Interaction			-.0895 (.5139)
Resp Race: Hispanic	.07715 (.1704)	.0447 (.1541)	-.0086 (.1592)
Hispanic: Interaction	-.5669 (.4583)		
Resp Race: Other	.1139 (.2273)	.247 (.2199)	.1332 (.2277)
Resp Race: Other: Interaction			-1.153 (.7615)
Income, $0 to $10,000	-.1483 (.2109)	.06386 (.1895)	-.0326 (.1976)
Income to $10,000 Interaction	.6943 (.4364)		
Income, $10,000 to $20,000	.1711 (.1516)	.133 (.1469)	.1236 (.1515)
Income, $20,000 to $30,000	-.0163 (.1381)	-.0173 (.1354)	-.0124 (.1377)
Income, $40,000 to $50,000	.1253 (.175)	.06457 (.1718)	.0728 (.1747)
Income, $50,000 +	.1316 (.1623)	.1333 (.1622)	.1181 (.1621)
Income $50,000+ Interaction		-1.197* (.7366)	
Resp Stressed		-.0917 (.1566)	-.0474 (.1599)
Resp Stressed: Interaction		2.997** (1.273)	
Resp Depressed	.3673*** (.1191)	.4351*** (.1258)	.3674*** (.1288)
Resp Thought about Suicide	.4270** (.2079)	.3943** (.2004)	.4811** (.2087)

Woman Pregnant	.2590 (.2446)		.2717 (.2439)
Family Status: Step	-.04365 (.1334)	-.006 (.137)	-.0647 (.133)
Family Status: Step: Interaction		-.9329* (.5264)	
Family Status: Single Parent	.1263 (.1629)	.1011 (.1396)	.1585 (.1629)
Child: Temper Tantrum	-1.4109* (.82)		
Child: Failing School		-4.686*** (1.808)	
Child: Discipline Problems at Home			-.3532 (.8068)
Cut 1	-.9654 (.3337)	-.945 (.33)	-.9421 (.3461)
Cut 2	1.798 (.3378)	1.765 (.3333)	1.795 (.3495)
Cut 3	3.583 (.3644)	3.5004 (.3562)	3.571 (.3752)
Observations	1810	1930	1810
LR-Stat	253.82 p: 0.000	255.33 p:0.000	233.65 p:0.000
Pseudo R^2	.0677	.0634	.0623

All three of these predictions are statistically significant in difference from zero with pseudo R^2's around.06. From the interacted ordered logit predictions I find the following coefficient estimates of non-interacted variables to be statistically significant in difference from zero across all three models (All of these estimates are statistically significant in difference from zero at least at the 10% level):

- Parent Gender (positive) – Being a female parent, as opposed to being a male parent, increases the probability that that parent turns to a higher level of violence, holding constant the influence of other variables. Females are not only more prone to abuse but also more prone to use higher levels of violence.
- Parent Age (negative) – As the parent gets older, the probability the selected parent uses higher levels of violence decreases, holding the influence of other variables constant.
- Child Age & Child Gender (negative) – As the child gets older, the probability they are exposed to higher levels of violence decreases, holding constant the influence of other variables. If the child is female, the probability that child is found in higher violence category also decreases, holding constant the influence of other variables.
- Abuse History (positive) – Parents who were abused by either parent as a teenager are more likely to use higher levels of violence, holding the influence of other variables constant.

- Race of the Parent: Black (positive) – If the respondent is African-American they are more likely to use higher levels of violence, holding constant the influence of other variables.
- Depression & Attempted Suicide (positive) – If a parent is depressed or has thought about killing themselves, that parent is more likely to use more higher levels of violence, holding constant the influence of other variables.

I again find many genetic and family history variables to be influential in increasing or decreasing the probability that higher violence levels are present. Many of the variables which determined the probability a parent uses abuse also determine the probability for a certain level of violence. Race and Depression have also come into play here. Race is another genetic trait that can not be controlled but may be serving as an indicator for income or education here. After checking correlation between race and other variables, I only found that race is somewhat correlated with low levels of income. One could easily argue that depression could be a predetermined disorder or a result of events in ones life. Either way, I expect this variable to make a parent more violent. I now present the significant coefficient estimates for the interacted variables.

The following variables are all interaction terms; showing how the presence of child behavior affects the decision of what type of abuse to use. All are significant at least at the 10% level of significance.

- Parent Age (Temper Tantrum & Failing School Interaction) – When a child either has a temper tantrum or fails in school, each year older the parent is increases the probability that the parent uses higher levels of violence, holding constant the influence of other variables. Younger parents are more likely to abuse and use higher levels when behavior is not considered, yet when behavior is a factor, the older parents are more likely to use higher levels of violence.
- Domestic Abuse Experience (Failing School Interaction) – I again find a contradictory relationship when behavior is factored in. In the failing school model, if the respondent's mother hit their father, this parent is more likely to use higher levels of violence, holding constant the influence of other variables. However, parents who have had this experience along with children who are failing school, are actually likely to use lower levels of violence of none at all. Again, I think this is a small sample issue.
- Abuse History (Failing School Interaction) – A parent who was abused by their father and has a child who is failing school is more

likely to use higher levels of violence, holding constant the influence of other variables. This is again consistent with initial expectations about abuse history.

- Stressed (Failing School Interaction) – Parents who feel stressed and have children who are failing school are more highly likely to use higher levels of violence, holding constant the influence of other variables. This is consistent with initial expectations.
- Child Failing School (negative) – Children who are simply failing are subjected to lower levels of violence or no violence, holding constant the influence of other variables.

The coefficient estimates for these statistically significant interaction terms demonstrate that behavior, especially if the child is failing in school, can dramatically alter what factors go into determining the level of violence choice the parent faces. While some of the variables are genetic, or based on experiences which could not be controlled; the interaction terms again demonstrate that factors such as stress factor into the decision about what kind of abuse a parent uses.

Interpretation of Results

From the results I find, based on the data from The Physical Violence in American Families Survey of 1984, the decision to abuse is based primarily on genetics and abuse history. Factors such as age and gender, both of the parent and the child, seem to be important factors in determining if parents abuse. Younger parents have younger children, and are less experienced. Also younger children can be a handful for these inexperienced parents and people have been known to snap when overwhelmed with frustration. Parental anger with a difficult child, sometimes results in abuse (Frude and Goss 1979, 331). Abuse history played a role in not only determining abuse, but also what kind of abuse, and how intense that abuse would be when interacted with certain child behaviors. Children learn how to be parents from their own parents and if a child is abused, it makes sense that it would be more likely to use abuse also. This relationship is parallel with a priori expectations. It is also important to note, mental illness, regardless of cause, is a factor that increases the probability of abuse.

While the genetic and family history variables play a role in almost every case of abuse, the impact of behavior also plays a role. The reviewed literature expected parental stress and income would be a factor in determining abuse. I conclude that stress and lower levels of income determine the presence of abuse, when certain behaviors are present. These two increase the odds of abuse significantly. Both the temper tantrum and failing school behaviors not only determined what factors increase the probability of abuse, when one of these behaviors are present, but also what type of abuse was more likely to be used. This demonstrates a certain child behavior, which can occur randomly such as a temper tantrum, increases the odds the parent uses abuse. Parental expectations play a critical role as well; this can be seen from the number of significant coefficient estimates for the failing school behavior. The coefficient estimates for the failing school interaction terms demonstrate that failing to meet parental expectations not only increases the probability the child is abused, but also the probability the child is exposed to a higher level of violence. I initially underestimated the role of parental expectations.

One factor I thought would increase the probability of a parent using abuse was alcohol consumption; however, it was never significant in any model. This demonstrates that alcohol may not be a determinant in child abuse, but possibly in numerous other problems. I expected income as well as family status to also play a larger role, which they did not. This could be due to the fact that lower income families are more likely to abuse with the presence of temper tantrums. I thought a similar relationship would occur with the family status variables.

This study has produced some interesting, albeit possibly inaccurate results. However, I find that there are certain genetic markers which trigger abuse, and there are numerous social variables which affect the decision to abuse and the choice of abuse type when a certain child behavior is present.

Conclusions

The goal of this paper was to examine the parental decision structure for child abuse. My initial hypothesis was that a child would behave, the parent would be forced to respond, and the decision to abuse would be based on social and genetic factors within the parent's life, as well as the manner in which the parent's perceived the child's behavior. I used McFadden's (1974) conditional logit model as a basis for my theory to show that the decision to abuse is based on factors both in the parent's life and in the child's life. I followed this with interacted logit and interacted order logit models, which used data from the Physical Violence in American Families Survey from 1984, to show that numerous biological and family history variables determine abuse regardless of behavior. The social variables such as stress, were found to increase the probability of abuse when the child behavior is considered.

Thus, I conclude that given the difficulty associated with predicting a problem as great as child abuse there is no specific set of variables which define an abuser over a non-abuser. There are only markers, which signal who may be more at risk to abuse. The decision to abuse is likely a snap judgment made by the parent. Parents probably do not premeditate abuse. As noted in the literature it is a combination of factors that triggers abuse. There are biological markers such as gender and age which put certain parents and certain children at higher risk than others. A parent who abuses is pushed to their limits by a certain child behavior or some other factor. I have found certain factors which are present in the abusing parent's life. A suggestion for further study would be to examine the effects of child abuse on children, for example if it increases the risk of teenage pregnancy, psychiatric disorders, or involvement in crime (Afifi, Brownridge, and Cox 2006, 1093-1103; Currie and Tekin 2006; Smith 1996, 131-142; Smith and Thornberry 1995, 451-481).

Appendix A

Variable Definitions of Independent Variables:

Gender of Respondent, Male=0 Female=1
Age of Respondent, Age must be equal to or above 18
Child Age- child must be under the age 18
Gender of Child, Male=0 Female=1
Respondent Father hit Mother, 0=No, 1=Yes
Respondent Mother hit Father, 0=No, 1=Yes
Respondent Arrested in previous year, 0=No, 1=Yes
Respondent Alcohol Use- measured in drinks per day
Black- respondent is African American, 1=yes, 0=no
Hispanic- respondent is Hispanic, 1=yes, 0=no
Other-respondent is other race, 1=yes, 0=no
Income variables, 1=respondent falls in specified category of income, 0=respondent does not fall in respective category
Stressed, 0=never felt stressed, 1=includes if respondent ever feels stressed
Depressed, 0=never felt depressed, 1=includes if respondent ever feels depressed
Thought about suicide, 0=never thought about suicide, 1=includes if respondent ever thinks about suicide
Respondent hit by mother as teen, 1=yes, 0=no
Respondent hit by father as teen, 1=yes, 0=no
Woman Pregnant, 1=yes, 0=no
Family Status, 1=respondent falls in specified category of family status, 0=respondent does not fall in respective category
Child Behavior Variables, 1=child has exhibited behavior, 0=child has not exhibited behavior

Summary Statistics of Independent Variables:

Variable	*Obs*	*Mean*	*Standard Deviation*	*Min*	*Max*	*Number of 1 values*	*Number of 0 values*
Gender: Respondent (Resp)	6002	.6106298	.4876481	0	1	3665	2337
Resp Age	5983	41.50343	14.31004	18	90		
Child Age	3360	8.447917	5.335733	0	17		
Child Gender	3360	.4985119	.5000722	0	1	1675	1685
Resp: Father hit Mother	5833	.1146923	.3186775	0	1	669	5164
Respt: Mother hit Father	5849	.0702684	.2556207	0	1	411	5438
Resp: Arrested in Last Year	5998	.0113371	.1058794	0	1	68	5930
Resp: Drinks Per Day	3895	2.309628	1.985605	1	40		
Resp: Hit by Mother as Teen	5720	.3916084	.4881526	0	1	2240	3480
Resp: Hit by Father as Teen	5605	.3295272	.4700835	0	1	1847	3758
Resp Race: Black	5913	.1432437	.3503508	0	1	847	5066
Resp Race: Hispanic	5913	.1219347	.3272381	0	1	721	5192
Resp Race: Other	5913	.0495518	.2170355	0	1	293	5620
Income, $0 to $10,000	5610	.141533	.3486016	0	1	794	4816
Income, $10,000 to $20,000	5610	.2292335	.4203772	0	1	1286	4324
Income, $20,000 to $30,000	5610	.2363636	.4248859	0	1	1326	4284
Income, $40,000 to $50,00	5610	.0950089	.2932534	0	1	533	5077
Income, $50,000 +	5610	.1244207	.3300903	0	1	698	4912
Resp: Stressed	6002	.8278907	.3775069	0	1	4969	1033
Resp: Depressed	6002	.7562479	.4293806	0	1	4539	1463
Resp: Thought about Suicide	6002	.0543152	.2266575	0	1	326	5676
Woman Pregnant	5747	.0351488	.1841718	0	1	202	5545
Family Status: Step	3415	.1314788	.3379727	0	1	449	2966
Family Status: Single Parent	3415	.1953148	.3965009	0	1	667	2748
Child: Temper Tantrum	3363	.1118049	.3151732	0	1	376	2987
Child: Failing School	3363	.0776093	.2675955	0	1	261	3102
Child: Discipline Problems at Home	3363	.0906928	.2872145	0	1	305	3058

Summary Statistics for Significant Interaction Terms (TT= Temper Tantrum, FS=Failing School, DP=disciplinary problems at home):

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*	*Number of 1 values*	*Number of 0 Values*
Resp Gender: TT	3363	.079096	.2699287	0	1	266	3097
Resp Age: TT	3356	3.748808	10.89398	0	62		
Drinks per Day:TT	2213	.2769	.9314	0	12		
Hispanic: TT	3334	.0173965	.1307632	0	1	58	3276
Income <$10,000	3201	.01905	.1367	0	1	61	3140
Resp Age: FS	3356	3.017282	10.62123	0	70		
Resp: Mother hit Father: FS	3292	.0085055	.091846	0	1	28	3264
Income> $50,000:FS	3201	.005935	.0768261	0	1	19	3182
Stressed: FS	3363	.068986	.2534681	0	1	232	3131
Resp: Hit by Father: FS	3168	.0309343	.1731672	0	1	98	3070
Step Family: FS	3363	.0133809	.1149164	0	1	45	3318
Resp Age: DP	3356	3.175805	10.29355	0	63		
Child Age: DP	3360	.8181548	2.97323	0	17		
Black: DP	3334	.0140972	.1179094	0	1	47	3287

Summary Statistics for Dependent Variables:

Abuse, 1=abuse was present, 0=otherwise

Abuse Type, 1=minor violence, 2=severe violence, 3= very severe violence,

0=otherwise

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
Abuse	3338	.6195327	.4855745	0	1
Abuse Type	3338	.7630318	.7207607	0	3

Tabulations of Dependent Variables:

Variable	*0*	*1*	*2*	*3*
Abuse	1270	2068		
Abuse Type	1270	1675	307	86

Cross-Tabulations of Independent Variables

Variable	*No Abuse*	*Abuse*	*Minor*	*Severe*	*Very Severe*
Resp Gender: Male	506	703	575	100	28
Resp Gender: Female	703	1365	1100	207	86
Child Gender: Male	591	1080	857	172	51
Child Gender: Female	678	986	816	135	35
Resp: Father hit Mother	143	328	237	67	24
Resp: Father did not hit Mother	1097	1692	1398	234	60
Resp Mother hit Father	82	215	152	43	20
Resp Mother did not hit Father	1159	1811	1492	256	63
Resp Arrested in Last Year	12	27	18	7	2
Res Not Arrested in Last Year	1256	2040	1656	300	'84
Resp Hit by Mother as Teen	395	935	710	169	56
Resp Not Hit by Mother as Teen	825	1064	910	127	27
Resp Hit by Father as Teen	324	747	576	125	46
Resp Not Hit by Father as Teen	871	1205	1003	165	37
Resp Race: Black	195	356	252	85	19
Resp Race: Not Black	1058	1700	1412	221	67
Resp Race: Hispanic	228	265	198	43	24
Resp Race: Not Hispanic	1025	1791	1466	263	62
Resp Race: Other	65	107	90	12	5
Resp Race: Not Other	1188	1949	1574	294	81
Income, $0 to $10,000	173	295	222	52	21
Income, $10,000 to $20,000	277	454	359	77	18
Income, $20,000 to $30,000	269	512	427	72	13
Income, $40,000 to $50,00	112	174	144	26	4
Income, $50,000 +	148	199	162	27	10
Resp Stressed	1007	1795	1454	270	71
Resp Not Stressed	263	273	221	37	15
Resp Depressed	882	1672	1329	269	74
Resp Not Depressed	388	396	346	38	12
Resp Thought about Suicide	58	140	97	34	9
Resp Never Thought about Suicide	1212	1928	1578	273	77
Woman Pregnant	24	100	85	15	0
Woman Not Pregnant	1175	1828	1485	267	76
Family Status: Step	176	271	218	46	7
Family Status: Non-Step	1094	1797	1457	261	79
Family Status: Single Parent	220	393	310	59	24
Family Status: Non-Single Parent	1050	1675	1365	248	62

Cross-tabulation of Child Age

Child Age	*No Abuse*	*Abuse*	*Minor*	*Severe*	*Very Severe*
>1	161	43	37	4	2
1	69	106	94	8	4
2	34	178	150	20	8
3	19	186	162	18	6
4	21	181	154	24	3
5	21	165	128	26	11
6	23	147	114	31	2
7	38	143	115	24	4
8	33	119	93	19	7
9	43	116	89	21	6
10	46	131	111	16	4
11	67	100	88	11	1
12	64	102	78	19	5
13	94	105	75	22	8
14	107	70	54	13	3
15	122	69	52	12	5
16	143	65	50	11	4
17	164	40	29	8	3

Cross-Tabulation of Respondent Drinks per Day

Drinks Per Day	*No Abuse*	*Abuse*	*Minor*	*Severe*	*Very Severe*
0	767	1189	964	178	47
1	12	63	44	15	4
2	10	72	55	14	3
3	7	43	33	7	3
4	1	14	11	2	1
5	2	8	5	3	0
6	4	11	8	2	1
7	0	1	0	1	0
12	0	1	0	0	1

Cross Tabulations of Selected Interaction Terms

Resp Gender: Male TT	1225	1848	1510	263	75
Resp Gender: Female TT	45	220	165	44	11
Hispanic: TT	15	43	31	9	3
Not Hispanic: TT	1238	2013	1633	297	83
Income <$10,000:TT	8	52	38	9	5
Income not <$10,000: TT	1182	1939	1575	289	75
Resp: Mother hit Father: FS	9	19	11	5	3
Resp: Mother did not hit Father: FS	1232	2007	1633	294	80
Income> $50,000:FS	11	8	5	3	0
Income not > $50,000:FS	1179	1983	1608	295	80
Stressed: FS	88	144	95	37	12
Not Stressed: FS	1182	1924	1580	270	74
Resp: Hit by Father: FS	26	72	45	19	8
Resp: Not Hit by Father: FS	1169	1880	1534	271	75
Step Family: FS	17	28	20	7	1
Not Step Family: FS	1253	2040	1655	300	85
Black: DP	10	37	24	11	2
Not Black: DP	1243	2019	1640	295	84

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A Current Microeconometric Assessment of the Racial Wage Gap in the United States

By David Krisch

I. Introduction

Minority groups in the United States promoted affirmative action legislation in the 1960s during the civil rights movement to help ease the inequalities suffered in their economic history. Many labor economists have sought since this time to study the effects of race, gender, and the effect of income – how it has changed and if the gap has closed. Existing literature uses many different econometric models to show how the effects of race, gender, age, occupation, educational attainment, and geographic location on an individual comparative basis. This paper will examine the effects of all of these variables jointly using an ordinary least squares (OLS) regression analysis.

Does race effect income according to the 2005 American Community Survey (ACS)? The ACS is 1 in 100 national survey that encompasses over 1.1 million households and 2.878 million individuals (Steven et. al.). Using multivariable OLS regression of such data will yield results that will provide an overall snapshot of the state of the modern labor economy and identify what problems our society has to economically overcome if an income gap between white males and minority groups still exists. Many other researchers have answered a similar question, however, the link between these variables on broad current level has not been drawn.

Many economists since the enaction of affirmative action have examined the effects of many different factors that influence income. Two major labor economists, Jacob Mincer and Peter Blau pioneered modern understanding of income labor economics that inspired further labor analysis. The major contribution of Mincer was to connect the modern theory of human capital to empirical survey data on income, and apply it to labor force inequality (Rosen 159). Mincer using a semi-log transformation analyzed the gender gap problem in the 1960s and 1970s by examining disparity among educational attainment (Rosen 159) (Bloom et.al. vi). This will be important in reviewing the results of the regression analysis, the use of showing how human capital will affect current data (apposed to the previous analysis that was rendered by Mincer), and the connection of the wage gap that will encompass both race and gender.

Blau's theory of status attainment describes that one can achieve a high social status (which is a measure of income economic status) by having an occupation which is associated with a higher economic benefit (Guan et. al. 115). Directly linked to cultural and individual microeconomic characteristics is higher social attainment (Guan et. al. 115). This theory will be used in conjunction with Mincer's work of human capital income analysis to both review current labor economics wage gap analysis and lay the framework for the economic model used in this paper (Guan et. al. 115).

Other literature examines the regional wage gap with particular focus on race. Bisping and Fain (2005) examine the theory of a labor queue, which orders demographics in terms of employer favorability on a regional and national level (Bisping et. al. 352). The results of this study show that there is no change in the order the labor queue and there is no significant change in the ordering of the queue on a national level (Bisping et. al. 358). In some specific regions, however, the existence of a racial gap appears eliminated (Bisping et. al. 358).

More recent wage gap analysis by Baumann (2005), examines using the Integrated Public Use Microdata Census project (IPUMS), if there has been a shift in the wage gap using time series data, specifically in Appalachian region of the United States (Baumann 416). This is in response to the historical evidence that suggests that individuals who live in this region have lower wages when compared to the rest of the country (416). The findings of this study show that the wage gap between the Appalachian region and that of the rest of the country has only decreased slightly from its level in 1970 to its level in 2000 (439). The focus of the econometric model in this paper will depart from the comparative nature of a shift in the wage gap over time, but focus on whether this gap currently exists between all races in geographic regions.

Further race-gender wage gap studies conducted recently narrow the specific hypothesis. Saunders (1995) examines the wage gap that exists on a regional, racial, gender, and occupational levels (Saunders 68). Findings indicate that black men average income decreased, while white men's average income increased over a ten-year period from 1979 to 1989 (68). Saunders' findings also indicate that black women gained ground when compared to white men (68). This is a refinement of the models previously discussed, but when examining the income gap between women, the same results are found then when comparing different races (69).

Antecol and Bedard (2002) conclude that minority women make substantially less than that of their white counterparts (Antecol 122). Neal

(2005) also supported this finding but insists that the wage gap is much higher then that was previously found in earlier analysis, such as the one conducted by Antecol and Bedard (Neal S1). The use of panel data in Neal's analysis and its inclusion of non-labor force individuals is the source of the underestimation of the wage gap (S3). This analysis will depart from Neal's method by examining only participants in the labor force market. These studies show how the Blau's theory of status attainment can relate to differing groups of minorities, while the differing human capital between gender and races support Mincer's theory of the connection between modern human capital and income.

Many economists have conducted studies looking at a number of different factors that influence income, but the analysis in this paper will seek to combine a number of different factors to give a general overview of the racial gap on differing regional levels. Marital status, age, region, occupation, gender, race, number of hours worked, and educational attainment all will be combined in OLS regression analysis to find whether such a gap still exists from 2005 ACS data. This is a departure from previous literature because of the larger scope of the analysis and current data for a more updated snapshot of the state of our economic equality.

Section II, Modeling and Data, contains the economic multivariable model that will be used in regression, how the hypothesis of the effects of race will be tested, description of the statistical properties of the ACS data variables used for this analysis, and how such data could influence the results. Section III, Empirical Results, will seek to explain the findings of the regression analysis. This section provides graphical analysis of the variables on a comparative level as well. Section IV will conclude with an overview of the findings and the impact of such findings.

II. Modeling and Data

The hypothesis that is being tested by this model is that: income has a negative (or equal) relationship to minority groups among differing geographical regions, educational attainment, marital status, occupation, gender, and age. The primary focus will be on regional affects, however, there will be a need to look at the influence of the other variables in order to truly understand the problem of income inequality in totality.

Evidence would support from the previous research that there is correlation between all of these variables and differences among these variables for different races compared to the historical Caucasian hierarchy that has dominated economically (Bisping et. al. 352). The status attainment theory that was offered by Blau in the previous section seem to confirm this finding and so does the research Bisping and Fain (2005) with the notion of a national labor queue (Bisping et. al. 352). The model will attempt to answer the question from a modern perspective using the most current economic data while trying to paint a complete picture of the factors that influence income.

In order to complete such a task, the dependent variable will be in logarithmic form to show the percent change in income for each of the independent variables. This is the same form of the semi-log transformation that Mincer provided in his earnings equation for the dependent variable (Rosen 159). In order to measure such effects of race, the coefficients of each of the independent variables tested in a multivariable analysis. If the coefficient is negative for an independent variable then the net effect on the percentage of income is negative while the opposite is true for a positive coefficient value.

Statistical significance of each of the variables and the model as a whole is incredibly important in both understanding and placing confidence in the findings. For individual variables, if the t statistic is greater than the critical value at n degrees of freedom at five percent significance then we can reject the null hypothesis that the coefficient is statistically insignificant. If the model, as a whole, is significant then the p value for the F statistic will be less than $\alpha=0.05$ and the null hypothesis that the coefficients are jointly insignificant can be dismissed.

The hypothesis being tested in this model would be confirmed if minority groups made less than or equal to that of Caucasians on a regional level, as well differing measures of human capital, and other differing measures of individual characteristics. In order to test such a hypothesis a multivariable analysis will be offered. This multivariable regression will be run with numerous dummy variables for measures of qualitative data (such as race, region, gender, marital status, occupation, ect.) versus quantitative data (such as educational attainment and age). There will be numerous interaction terms with race against occupation, education, gender, age, marital status, geographical region, and educational attainment. In order to correct for perfect multicollinearity, one dummy variable for each group of the dummy variables that will be created must be excluded. The excluded dummy variables will be reflected in the constant coefficient (β_0) as well as the intercept value of the equation estimation. The model is as follows:

lnIncome = f *(race, gender, usual hours worked, region, education, education^2, age,*

*age^2, occupation, marital status, race*gender, race*usual hours worked, race*region, race*education, race*education^2, race*age, race*age^2, race*occupation, race*marital status)*

The above model compares the percentage change in income of a single, white, male, residing in the East North Central Region, and is in a management occupation against the other dummy variables that are in the equation.[1] The constant is the comparative term to the rest of the dummy variables.

The other quantitative measures: age, years of education, and usual hours worked is a measure the marginal effect on the percentage change of income. Two variables are specifically notable. The variables of age and years of education both have a squared term counterpart. This occurs because usually these two variables do not move in a linear relationship as they increase, but as an exponential relationship (specifically as a quadratic). The marginal effect of age is the sum of $\beta_2+2\beta_3$(Age). This value was computed by taking the derivative of the age variables. The same transformation would be applied to education to find its marginal effect with respect to income.

The interaction terms that the economic model contains compare two changes from the constant, omitted dummy variables term. Notice that these interaction terms encompass the race (black, white, other) and other variables in the equation. This economic model is comprehensive in an attempt to precisely identify the factors to income in a hope to identify racial problems. The model is similar to that proposed by Mincer to measure wage and encompasses measures of status attainment by occupation proposed by Blau (Rosen 159) (Guan et. al. 115). This should produce a modern economic model to estimate the overall affects of race on income in a hybridized OLS estimation model. If the hypothesis is confirmed then the race and racial interaction terms should produce lower (or equal) coefficients. This would prove that there is the existence of a racial wage gap today and the examination of the regional affects could suggest where major problems still exist as compared to others. [2]

The data used for this examination of income with respect for race has its limitations. The model that was proposed in the previous section only examines one part of the evidence that can be used in determining the effects of

1 Full Equation in Appendix A

2 Note that time series analysis will not be offered but simply a cross sectional snapshot which cannot empirically show a shift in the wage gap without the use of a Chow Test on Panel Data.

income distribution. The data for this study was gathered from the Integrated Public Use Microdata Census project (IPUMS), which organizes and codes individual United States survey data (Steven et. al.). The particular data that will be examined in this study will use American Community Survey (ACS) of 2005. The ACS is a 1 in 100 national survey that encompasses over 1.1 million households and 2.878 million individuals that will prove to be essential to the validity of the findings because of the number of observations (Steven et. al.). Also if note is that this data is cross sectional data, which provides for a snapshot of the wage gap currently. This interpretation from the data and evidence should not be construed to show the shift of such a curve but how it affected individuals in 2005.

The assumption that all surveys are answered truthfully and completely is a flawed one. Many individuals who answer such surveys do not always answer the question that is being answered or the data is not always answered truthfully because of a privacy concern. This could produce bias or inconsistent results. An optimal data set would contain complete and actual data on each of the individuals surveyed in order to lead to complete, unbiased, and consistent results for the OLS regression. However, the sheer number of observations and the reliability of the reputable American Community Survey and IPUMS should decrease the probability of flawed results.

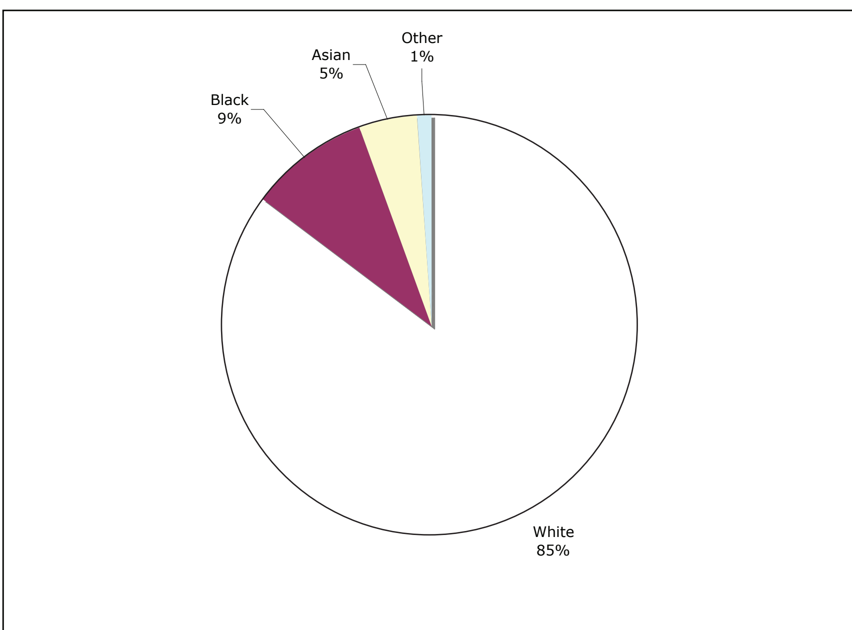
As was stated in previously, this data will incorporate dummy variables, whose observations will take either a 1 or 0. The value of 1 will be assigned if the individual being surveyed fits into the particular categorical variable or 0 if they do not. This measure will be applied to cross sectional, discrete, qualitative data while the continuous variables will take a specific input from the values observed. For instance age for an individual could be 45 in contrast to the variable female which would take a value of 1 in the individual was female or 0 if the individual was male.

The number of observations for this particular data set that is being regressed is 1,346,250 and the changes for the regression OLS estimates will be in percentage changes with respect to the percentage change in income (and against the constant term). Statistically insignificant terms, probability values for the t statistic less than $\alpha=0.05$, will not be reflected in the results but this will be noted as each section of the results is discussed and in Appendix B.

The dependent variable is the natural log of the total amount of income and wage. Any observations for an individual who makes an income of zero will be dropped from the data because this analysis will focus on factors of the change in percent of income in the current labor force. This will be important when also examining the factor of age. The variable age was dropped if the individual was under the age of 18 or over the age of 65. The mean income of the data set was 39,624.42 and the mean age of 40.795.

The independent variables used in the OLS regression for race where divided into four dummy variables. The first variable white, takes a value of 1 if the variable is white or 0 for non-white. The variable "White" is defined by those who are both Caucasian and Hispanic (Steven et. al.). The variable "white" will be omitted from the regression, will be included in the constant, and therefore comparative to all the other dummy variables. The variable "Black" includes all individuals who are of African American descent and identify themselves as black (Steven et. al.). The variable "Asian", reflect those individuals who are Asian or Pacific Islander (Steven et. al.). The variable "other" is for those who are not included in the category of white, black, or Asian. It is important to note that for this analysis, added to this category are the indigenous population (Native Americans) from the original survey results reported by the ACS and organized by IPUMS.

Figure 1. Frequency of Race Survey Data



The graph above shows the break down of the percentages of individuals surveyed and included in this regression. The number of observations as stated above for this data set was 1,346,250 and for this data set the amount of African American individuals that were sampled shows that there could be some bias in regression results. According to Census Scope, which is a product of the Social Science Data Analysis Network, the African American population accounts for 12.1% of the total population for the 2000 United States Census Survey ("CensusScope -- Demographic Maps: African-American Population"). Such a discrepancy in the representation of the population through this sample could lead to some biased and inconsistent results, which would not reflect the true β for the estimation.

The regional variables were divided into 9 different geographical regions in dummy variables as designated by the United States census and IPUMS classification (Steven et. al.). The East North Central region will be omitted from the regression because of perfect multicollinearity among dummy variables. The regions in the data are as shown in Figure 2 below, along with mean income and number of observations for each of the specific regions.

Figure 2. Regional Mean Income and Wage Observations

Region	Encompassed States	Mean Income[39]	# of Obs.
New England	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont	46,500.53	67,690
Middle Atlantic	New Jersey, New York, Pennsylvania	44,047.26	181,847
East North Central	Illinois, Indiana, Michigan, Ohio, Wisconsin	37,594.00	219,726
West North Central	Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota	34,401.52	94,244
South Atlantic	Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, West Virginia	40,018.01	260,214
East South Central	Alabama, Kentucky, Mississippi, Tennessee	33,782.85	78,129
West South Central	Arkansas, Louisiana, Oklahoma, Texas	36,165.84	145,108
Mountain	Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming	37,296.81	93,600
Pacific	Alaska, California, Hawaii, Oregon, Washington	43,233.47	205,692

Notice that the omitted variable East North Central, has a mean income of 37,594.00 that lies somewhat in the middle of the data set which will be a good measure for comparing differing regions in the OLS regression analysis.

Occupation, marital status, and gender are generated dummy variables from the original equation. There are 25 occupations that are incorporated into the data with varying categories and 24 will be used in the regression. The variable "management" has a relatively high mean of 74,927.50 and a standard deviation of 61,516.55. This variable will be omitted from the regression and the definitions of the other occupation variables are offered in Appendix C. Marital status has five different dummy variables (single, married, divorced, widowed, and separated) and the variable “single” is dropped from the regression equation. The variable “single” has the lowest average income of all of the variables, 24,994.82, while those who are married have the highest average income, 46,950.95. By no means is this a surprising factor, because those who are older tend to be married and also have a higher income. The final dummy variable gender, are obviously divided into male and female variables. The variable male has a mean income of 48,394.13 and a standard deviation of 47,672.79 while females have a mean income of 30,429.30 and a standard deviation of 30,575.10. A clear gender gap that still exists and the variable “male” will be omitted from the regression.

Figure 3. Summary Statistics for Continuous Data[3]

Variable	# of Obs.	Mean	Std. Dev.	Min	Max
Years of Ed.	1,346,250	13.4900	2.5899	0	20
Age	1,346,250	40.7951	12.5175	18	65
Usual Hours Worked	1,346,250	39.8141	11.9730	1	99

The variable “Years of Education” was recoded in order to accommodate for preschool and kindergarten education. The number of years of education and the percentage change in income has a positive correlation of 0.315 and the mean education that an individual receives in the survey is 13.49 years as shown above in Figure 3. Education is a large component to income which is reflected in the positive correlation in the percentage change in income and the average individual in the data receive their high school diploma. The relationship between human capital (years of education being one factor in this case) and amount of income one receives is an already time tested model by Mincer (Rosen 159).

The final variable examined, the amount of hours usually worked in a workweek, also has opposite correlation effects on the percentage change in income. The amount of income hours worked increases as income does. The average amount of hours worked for the data set is 39.8141, shown in Figure 3, the standard workweek. This is not surprising and matches the intuition about the amount of hours worked in the American workweek.

III. Empirical Results

The full results of the regression analysis for the model that was in Section II is displayed in Appendix B. The Breusch-Pagan test statistic of 44,583.32 for the equation estimation identified the problem of heteroskedasticity. This

3 Values will be rounded to four decimal places.

BP test statistic has a p value of 0.000 and because it is less than $\alpha=0.05$, the null hypothesis of homoskedasticity can be rejected. This has prompted the regression to be re-estimated with robust standard errors using the white correlation matrix to correct this problem. With the correction, the first of three different results of particular interest will be discussed in detail, after significance of the individual variables and the model as a whole is discussed.

The F test statistic, which tests that all of the coefficients are significantly different than zero, yielded a result of 5,696.86. The p value for the F statistic for this equation is equal to 0.000 which is less than $\alpha=0.05$ so we can reject that the coefficients of the model are jointly insignificant. This result is reflected in Appendix B. Each individual variable was also tested for significance by calculating a t test statistic from the regression results. The p values for the t test statistic that were greater than $\alpha=0.05$ are reflected in Appendix B without asterisks.

For instance, the p value of the t statistic for the variable "other" indicates that there is not a difference in the nominal income of an individual who's race is considered "other" against the constant white individual with all of the same characteristics besides race. The same is true of occupational, marital status, regional, and continuous (usual hours worked and years of education) variables that are interacted with race. The interaction variables that were interacted with age were dropped for reasons of perfect multicollinearity and are not reflected above for the races of Asian and other. This lack of significance for the variable of "other" is in conflict with the original hypothesis that being non-white has a negative impact on an individual's nominal income. This will be compared to the results found for significant variables in the preceding part of this section and in the conclusion. It should also be mentioned that in order to combat omitted variable bias the variables that are in Appendix B without asterisks are included in the final regression. Omitting such variables could cause biased estimates of the parameters.

The evaluation of the R-squared term is essential to understanding the prediction capability of the model as a whole. The R-squared term reflects the proportion of the variance of the dependent variable that can be explained by the independent variables ("Annotated Stata Output: Regression"). The R-squared value for the equation that was regressed from the model in Section II is 0.4902. This would indicate that 49.02% of the variance in the percent change in income could be predicted from the independent variables ("Annotated Stata Output: Regression"). This is not a bad measure of fit for how well the model is at predicting income assuming that there are many different variables that can be used to predict income which cannot be measured, such as drive to succeed and ambition. This R-squared value vastly improved when the variable of occupation was added to the regression and therefore occupation improved the prediction of the dependent variable, which is to be expected.

The continuous variable "years of education" produced a value of -0.0235 and a value of 0.0042 for the variable "years of education^2". This relationship between income and education in quadratic terms is the same function that Mincer used in his earnings equation to examine the gender wage gap in the United States (Rosen 159). Such will be applied here to look at the differences in racial variables with individuals who have the same amount of education. In Figure 4, the table reflects the significant interaction terms between race and years of education. Also, there are the coefficients for the variables of race in the East North Central Division. This analysis will first encompass how race effects income against education in the East North Central Division and then examine how these effects are administered for other regions of the United States in the same comparative nature against the constant term with the same amount of education.

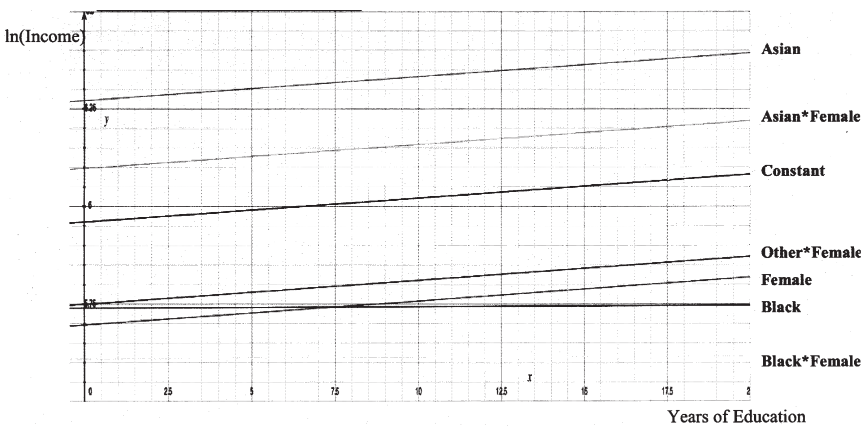
Figure 4. Statistically Significant Regression Results for Education, Race, and Gender in the East North Central Region (and applicable interactions)[4]

Variable[2]	Coefficient	Robust Std. Error
Year of Education	-0.0235	0.0015
Year of Education2	0.0042	0.0001
Black*Years of Education	-0.0194	0.0058
Black*Years of Education2	0.0010	0.0002
Black	-0.2200	0.0531
Asian	0.3113	0.0417
Female	-0.2630	0.0019
Black*Female	0.1326	0.0065
Asian*Female	0.0888	0.0079
Other*Female	0.0528	0.0208
Constant	5.9599	0.0148

4 Not included in the findings are the insignificant variables which had a p value for the t statistic greater than α=0.05 which are in Figure 4.

Figure 4 contains some interesting results go to disproving the hypothesis of being a non-white male has a negative affect on income in this particular region. Asian males and females have a larger change in income than the constant white single male term, which is reflected in the constant variable. To see the results more clearly, Figure 5 has a linear representation of the marginal change in income on one additional year of education.

<u>Figure 5. Marginal Effect of Education on Managerial Income by Race and Gender in the East North Central Division</u>



What should be noted in this graphical depiction is the intercept of each of the linear equations graphed with respect to the constant. Single managers who reside in this region are all compared with education for differing variants for race and gender. The line with the lowest intercept is the black female. The average black single female manager in this region makes 33.10% less than the constant comparative term whereas the white female makes only 26.30% less than the constant term. The black female makes substantially less than her white counterpart.

The trend for Asian individuals receiving more income for an increase in education transcends gender. The Asian male makes 31.11% more than the constant term and the Asian female only makes 13.11% less than the constant term. Both of these terms show that Asians make more on average than their white counterparts when compared to gender. This is a clear depiction that the gender gap exists, however, Asian individuals receive the highest utility out of all of the racial groups.

The racial wage gap still clearly exists between black and white individuals with the same constant comparative dummy variable terms. Black individuals make 22% less than the constant comparative term in this equation. This indicates that Asian women, "other" women, white males, and Asian males make more than a black male in a managerial position for the same amount of education in the East North Central Region. These groups receive more income than the black male for each additional year of education. Such a result is discouraging when examining the racial wage gap divide in the United States and reinforces the hypothesis that such a wage gap does still exist.

The same comparisons can be made against other continuous non-dummy variables in the OLS regression results. The coefficients for the usual hours worked, age, and age^2 is shown below in Figure 6.

<u>Figure 6. Continuous Coefficient Estimations for Usual Hours Worked, Age, and Age^2</u>

Variable	Coefficient	Robust Std. Error	T Statistic
Age	0.1132	0.0005	220.0100
Age2	-0.0012	0.0000	-196.6000
Usual Hours Worked	0.0389	0.0001	340.5800
Asian*Usual hours worked	-0.0058	0.0005	-12.3700

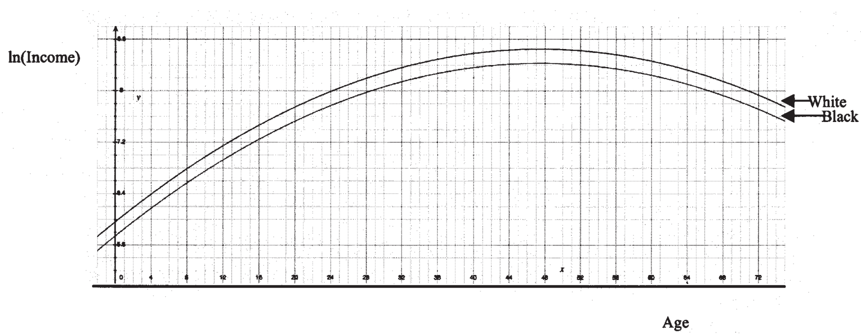
Omitted from Figure 6 are the interaction variables between race and age dropped for reasons of multicollinearity. Also omitted from Figure 6 is the interaction variables Black*Usual Hours Worked and Other*Usual Hours Worked, because of lack of significance. These continuous variables can be used with respect to the constant and the use of the other dummy variables to calculate intercepts and find the effect of usual hours worked and age on income. The amount of hours worked does positively increase the amount an individual earns by 3.89% for each additional hour worked and this number decreases by 0.58%[5] for each additional hour that an Asian individual works. The increase in the amount an individual earns being positively correlated to income is not surprising and are both supported by the previous research done in labor economics by Mincer, Blau, and others previously cited in the literature review ((Rosen 159) (Guan et. al. 115) (Bisping et. al. 352)). The interesting result is the effect of being Asian and the number of hours worked on the constant term. This gain in earnings for other races is higher for the number of hours

5 Total Marginal Effect for an Asian individual is 3.31% for Hours worked within a workweek.

worked when compared to the Asian individual. Such a finding is paramount in balancing the effects of income and race with continuous variables (like the results found for years of education).

The variables for age and age^2 create a parabolic effect, which is shown in Figure 8. (Guan et. al. 115). The marginal effect of one year of age is β_1 + 0.1131896 +2*-0.0011914(Age) by taking the derivative of the age function, but its quadratic form is graphed in Figure 7.

Figure 7. Effect of age on the percentage of income in East North Central region for the constant white single male manager in the East North Central region compared with a black individual with the same characteristics.



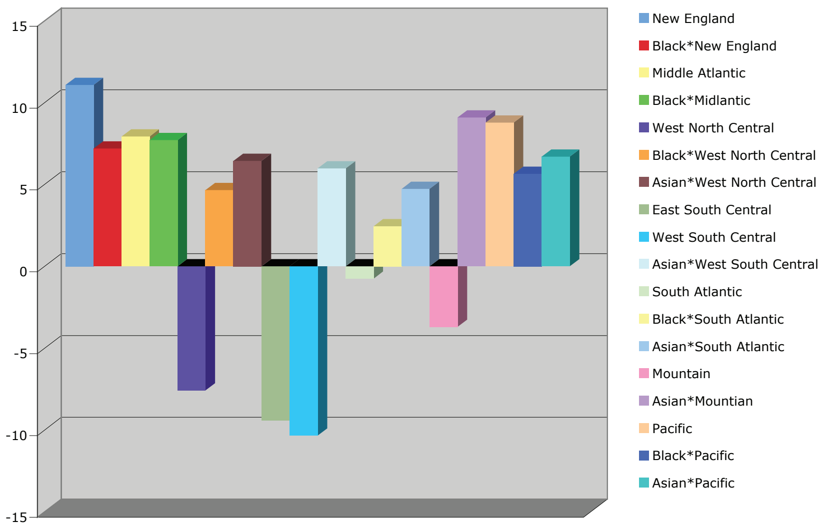
We see this in Figure 7, with the maximum point of the quadratic age function residing at 47.50. An individual's income after this point will not increase as age increases. Also, shown in Figure 7 is the age quadratic function for a black individual with the same characteristics in the East North Central Region. Here the wage gap between the two groups can clearly be seen, as was the case in the analysis for educational attainment. Focusing on the results of the amount of education and the percentage change in income is the original function that Mincer used in his original analysis (Rosen 159). Both education and age are measures of human capital, however, the results of the years of education analysis provide a more in-depth analysis and allow for interaction terms without multicollinearity.

The regional effects on income are interesting especially when looking at the variables of race. Such are interesting and help to pinpoint specific areas in which progress has been made in closing the wage gap and comparing how minorities fair in these regions. Figure 8 shows the regression results from statistically significant variables of the percentage change in income when compared to the constant East North Central region with all of the same constant dummy variables except for race. It is important to note that the significant interaction terms are in terms of the percentage difference in income when compared to that specific race variable for the East North Central Division. For instance the interaction variable for "Black*Middle Atlantic" is the percentage change between an individual who is Black, resides in the East North Central Region, Single, and working in a managerial position. Such results are illustrated more clearly in Figure 10, which depicts the percentage change using a histogram.

Figure 8. Statistically Significant Regional Effects on Income (with race interaction) compared to the constant regional variable East North Central.

Region	Coefficient	Robust Std. Error
New England	0.1109	0.0037
Middle Atlantic	0.0793	0.0028
West North Central	-0.0758	0.0033
East South Central	-0.0941	0.0038
West South Central	-0.1034	0.0031
South Atlantic	-0.0076	0.0026
Mountain	-0.0371	0.0035
Pacific	0.0878	0.0028
Black*Middle Atlantic	0.0770	0.0110
Black*New England	0.0720	0.0185
Black*West North Central	0.0465	0.0182
Black*South Atlantic	0.0245	0.0093
Black*Pacific	0.0565	0.0130
Asian*West North Central	0.0644	0.0270
Asian*West South Central	0.0598	0.0186
Asian*South Atlantic	0.0473	0.0164
Asian*Mountain	0.0910	0.0210
Asian*Pacific	0.0670	0.0142

Figure 9. Managerial Income Percentage Change with Respect to the Constant Term of East North Central White Single Male



The graph in Figure 9 and the table in Figure 8 provide interesting results for analysis. We can see for the New England Region that the wage for a white individual increases by 11.09%, however, a black individual with the same microeconomic characteristics in the same region only has 7.20% increase in wage in income from the black individual in the East North Central Region. The persistence and widening of the wage gap in the New England Region is clear when looking at the comparative variables. If the black individual had received the same increase in salary as the white individual then the wage gap would be the same as East North Central division with the same characteristics. This is not the case however, with a discouraging increase in the differences in wage with an increase of 3.89% in the racial wage gap. This is in contrast to the West North Central Division.

The interaction terms between Asian, Black, and West North Central Division are statistically significantly. The regional variable West North Central has decreased by 7.58% for the amount of income received for a white individual with the same microeconomic characteristics. An Asian individual's income with the same characteristics has an increased income of 6.44% and a black individual has an increased income by 4.65% when compared to the racial variables for the East North Central region depicted in Figure 4. The more significant of the two findings is not the increasing of the income gap between Asians and Whites in the West North Central Division but the decreasing of the income gap between Black and White individuals with the same characteristics when compared to the East North Central Region. Such a gap leaves black individuals with only a 9.77% difference in wage with their white counterparts in this region. This is a 12.23% narrowing from the 22.00% gap in the East North Central Division between a black and white individual with the same characteristics.

Two elements should be reiterated. The first element that should be noted is the absence of the variable "other" in this particular variable analysis. This would suggest that this variable and its interaction terms are not significantly different from the constant term. This applies equally to the other variables for interaction that were not included in Figure 8. The second element that should be noted is the relationship that can be formed between the dummy variables, which were not discussed (marital status and occupation), the interaction of these variables with the race dummy variables, and the interaction of these variables with the continuous variables discussed in the first part of this section.

The statistically significant marital status variables, in Appendix B, can be applied in the same way for analysis of both interaction and non-interaction terms of the variables with respect to the constant. For instance an individual, who is white, married, resides in the East North Central Division, and a manager makes 15.11% more than a single individual who has the same characteristics. These terms could also appear in the graph of Figure 5 to show how a constant amount of education can affect the overall percentage of an individual income and how this affects their marginal effect on income. This same approach can be applied to occupation as well.

The implementation of comparing multiple different incomes for occupational variables can be applied for analysis to gain both an industry and skill based analysis. An individual who is white and works in the computer industry makes 11.83% more than the manager in the East North Central region with the same microeconomic characteristics. A black individual in the computer industry makes only 10.13% more than a black manager in the East North Central region with the same microeconomic characteristics. This is further evidence that a racial gap does exist between individuals in other high skilled labor markets. This same analysis can be applied to non-skilled based jobs by applying the findings in Appendix B.

IV. Conclusion

By combining the theories previously explored in this field labor economics, a suitable model was formed in order to diagnose and analyze the current state of the racial wage gap (Rosen 159) (Guan et. al. 115). Through the use of ACS data and multivariable OLS regression, an in-depth analysis of variables that pertain to the percentage of income was completed in Section III. Evidence in this section shows that there is an existence of a racial and gender based wage gap in the United States both on a regional and national level, however, this is an oversimplification of the problem.

The literature review shows that a racial wage gap still exists on a national level but not on regional level from Bisping and Fain's findings (Bisping et. al. 352). The previous review of analysis show that there is an existence of an income gap between African American individuals and white single manager individuals in the East North Central Region of the United States. Being an African American has a negative effect on income. The gender gap was also shown in this analysis as well. Also being a white, black, other, or Asian female has a negative effect on income against their microeconomic identical male counterpart.

The surprising finding of this study shows that there is a wage gap between Asian individuals and white individuals with the same microeconomic characteristics. This might be the discrepancy that was found on the regional level in East North Central region in this study and that found by Bisping and Fain's findings (Bisping et. al. 352). Breaking the groups down into more specific classifications in and making this a broad overall snapshot from the most recent data available were the most important distinctions from how this study differed from other previous analysis.

Even though this model is comprehensive, adding more variables and interaction terms could give clearer results for future studies. This would then broaden the scope of the study and provide more information on other variables that pertain to income such as place of origin or weight. Also, classifying groups by ethnicity *and* race could provide more accurate results if the data sample was an accurate representation of the United States population. The analysis provided in this study would be most useful in showing how we need as a society to correct the disparities between African Americans, females, and white males with the same microeconomic characteristics. Only through conscience effort can this goal be achieved through a national and regional level. Such was the attempt of Affirmative Action but it is clear by this analysis that the goal was not accomplished in 2005.

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Appendix A. Full Equation Regressed

$$
\begin{aligned}
\ln\text{Income}_i = {} & \beta_0 + \beta_2\text{Age} + \beta_3\text{Age}^2 + \beta_4\text{Usualhoursworked} + \beta_5\text{MiddleAtlantic} + \beta_6\text{EastNorthCentral} + \\
& \beta_7\text{WestNorthCentral} + \beta_8\text{EastSouthCentral} + \beta_9\text{WestSouthCentral} \\
& +\beta_{10}\text{SouthAtlantic} + \beta_{11}\text{Mountain} + \beta_{12}\text{Pacific} + \beta_{13}\text{Black} + \beta_{14}\text{Asian} + \beta_{15}\text{Other} + \\
& \beta_{16}\text{Female} + \beta_{17}\text{MarriedSpouse} + \beta_{18}\text{Widowed} + \beta_{19}\text{Seperated} + \beta_{20}\text{Divorced} + \\
& \beta_{21}\text{YearsofEducation} + \beta_{22}\text{YearsofEducation}^2 + \beta_{23}\text{Buisopp} + \beta_{24}\text{FinancialSpecialist} + \\
& \beta_{25}\text{Compmath} + \beta_{26}\text{EngArch} + \beta_{27}\text{Science} + \beta_{28}\text{CommunitySocial} + \beta_{29}\text{Legal} + \beta_{30}\text{Edocc} \\
& +\beta_{31}\text{ArtMediaSports} + \beta_{32}\text{HealthCarePrac} + \beta_{33}\text{Healthcaresupport} + \beta_{34}\text{Protect} \\
& +\beta_{35}\text{Food} + \beta_{36}\text{CleanMaintain} + \beta_{37}\text{PersonalCare} + \beta_{38}\text{Sales} + \beta_{39}\text{OffAdSup} \\
& +\beta_{40}\text{FarmFish} + \beta_{41}\text{Construction} + \beta_{42}\text{Extraction} + \beta_{43}\text{InstallMaintRepair} \\
& +\beta_{44}\text{Production} + \beta_{45}\text{Transportation} + \beta_{46}\text{Military} + \beta_{48}(\text{Black*MiddleAtlantic})_i + \beta_{49} \\
& (\text{Black* EastNorthCentral})_I \ldots + \beta_{55}(\text{Black*Pacific})_i + \beta_{56}(\text{Asian*MiddleAtlantic})_i + \\
& \beta_{57}(\text{Asian*EastNorthCentral})_I \ldots + \beta_{63}(\text{Asian*Pacific})_i + \beta_{64}(\text{Other* MiddleAtlantic}) \\
& {}_i + \beta_{65}(\text{Other*EastNorthCentral})_I \ldots + \beta_{71}(\text{Other*Pacific})_I + \beta_{72}(\text{Black*MarriedSpouse}) \\
& {}_i + \beta_{73}(\text{Black*Widowed})_I \ldots + \beta_{75}(\text{Black*Divorced})_i + \beta_{76}(\text{Asian*MarriedSpouse}) \\
& {}_i + \beta_{77}(\text{Asian*Widowed})_I \ldots + \beta_{79}(\text{Asian*Divorced})_i + \beta_{80}(\text{Other*MarriedSpouse}) \\
& {}_i + \beta_{81}(\text{Other*Widowed})_I \ldots + \beta_{83}(\text{Other*Divorced})_i + \beta_{84}(\text{Black*Yearsofed})_i + \\
& \beta_{85}(\text{Black*YearsofEducation}^2)_I + \beta_{86}(\text{Asian*Yearsofed})_i + \beta_{87}(\text{Asian *YearsofEducation}^2)_I \\
& +\beta_{88}(\text{Other*Yearsofed})_i + \beta_{89}(\text{Other*YearsofEducation}^2)_I + \beta_{90}(\text{Black*Female})_i + \beta_{91}(\text{Asian*} \\
& \text{Female})_{I\,+}\beta_{92}(\text{Other*Female})_i + \beta_{93}(\text{Black*Age})_i + \beta_{94}(\text{Black*Age}^2)_I + \beta_{95}(\text{Asian*Age}) \\
& {}_i + \beta_{96}(\text{Asian*Age}^2)_I + \beta_{97}(\text{Other*Age})_I + \beta_{99}(\text{Other*Age}^2)_I + \beta_{100}(\text{Black*Buisopp}) \\
& {}_i + \beta_{102}(\text{Black*FinancialSpecialist})_I + \ldots + \beta_{124}(\text{Black*Military}) + \beta_{125}(\text{Asian*Buisopp}) \\
& {}_i + \beta_{126}(\text{Asian*FinancialSpecialist})_I + \ldots + \beta_{149}(\text{Asian*Military}) + \beta_{150}(\text{Other*Buisopp})_i + \\
& \beta_{151}(\text{Other*FinancialSpecialist})_I + \ldots + \beta_{171}(\text{Other*Military})
\end{aligned}
$$

Appendix B. Full Regression Results (*Statistically Significant at the 5% Level)

Variable	Est. Earnings Effect	Robust Std. Err.	P>t
Constant	5.9599*	0.0148	0
AGE:			
Age	0.1132*	0.0005	0
Age^2	-0.0012*	0.0000	0
Black*Age	0.0034	0.0018	0.056
Black*Age^2	0.0000	0.0000	0.814
USUAL HOURS WORKED:			
Usual Hours Worked	0.0389*	0.0001	0
Asian*Usual Hours Worked	-0.0058*	0.0005	0
Black*Usual Hours Worked	-0.0007	0.0004	0.085
Other*Usual Hours Worked	-0.0023	0.0012	0.051
EDUCATIONAL ATTAINMENT:			
Years of Education	-0.0235*	0.0015	0
Years of Education^2	0.0042*	0.0001	0
Black*Years of Education	-0.0194*	0.0058	0.001
Black*Years of Education^2	0.0010*	0.0002	0
Asian*Years of Education	-0.0047	0.0046	0.301
Asian*Year of Education^2	-0.0004	0.0002	0.062
Other*Years of Education	-0.0186	0.0122	0.129
Other*Years of Education^2	0.0002	0.0005	0.781

REGION:			
New England	0.1109*	0.0037	0
Middle Atlantic	0.0793*	0.0028	0
West North Central	-0.0758*	0.0033	0
East South Central	-0.0941*	0.0038	0
West South Central	-0.1034*	0.0031	0
South Atlantic	-0.0076*	0.0026	0.004
Mountain	-0.0371*	0.0035	0
Pacific 0.0878*		0.0028	0
Black*Middle Atlantic	0.0770*	0.0110	0
Black*New England	0.0720*	0.0185	0
Black*West North Central	0.0465*	0.0182	0.011
Black*East South Central	-0.0096	0.0119	0.419
Black*West South Central	-0.0032	0.0112	0.776
Black*South Atlantic	0.0245*	0.0093	0.009
Black*Mountain	0.0388	0.0208	0.062
Black*Pacific	0.0565*	0.0130	0
Asian*Middle Atlantic	-0.0085	0.0162	0.599
Asian*New England	0.0246	0.0221	0.267
Asian*West North Central	0.0644*	0.0270	0.017
Asian*East South Central	0.0443	0.0327	0.175
Asian*West South Central	0.0598*	0.0186	0.001
Asian*South Atlantic	0.0473*	0.0164	0.004
Asian*Mountain	0.0910*	0.0210	0
Asian*Pacific	0.0670*	0.0142	0
Other*Middle Atlantic	0.0623	0.0408	0.127
Other*New England	0.0088	0.0485	0.855
Other*West North Central	-0.0871	0.0450	0.053
Other*East South Central	0.0015	0.0550	0.978
Other*West South Central	-0.0212	0.0342	0.536
Other*South Atlantic	0.0201	0.0357	0.573
Other*Mountain	-0.0427	0.0346	0.216
Other*Pacific	-0.0625	0.0336	0.063
RACE:			
Black	-0.2200*	0.0531	0
Asian	0.3113*	0.0417	0
Other	0.1420	0.1018	0.163
GENDER:			
Female	-0.2630*	0.0019 0	
Black*Female	0.1326*	0.0065 0	
Asian*Female	0.0888*	0.0079 0	
Other*Female	0.0528*	0.0208 0.011	
MARITAL STATUS:			
Married	0.1511*	0.0023	0
Widowed	0.0729*	0.0072	0
Separated	-0.0368*	0.0067	0
Divorced	0.0792*	0.0032	0
Black*Married	0.0089	0.0070	0.202
Black*Widowed	-0.0250	0.0195	0.199
Black*Separated	0.0272	0.0144	0.06
Black*Divorced	0.0015	0.0093	0.873
Asian*Married	-0.0251*	0.0085	0.003
Asian*Widowed	-0.0082	0.0321	0.798

Asian*Separated	0.1047*	0.0330	0.001
Asian * Divorced	0.0848*	0.0163	0
Other*Married	0.0573*	0.0203	0.005
Other*Widowed	0.1001	0.0614	0.103
Other*Separated	0.0231	0.0523	0.658
Other*Divorced	0.0479	0.0283	0.09
OCCUPATION:			
BusinessOp	-0.0412*	0.0055	0
Financial	-0.0242*	0.0053	0
ComputerMath	0.1184*	0.0049	0
Engineering	0.0292*	0.0049	0
Science	-0.1913*	0.0079	0
Community	-0.4519*	0.0062	0
Legal	0.0011	0.0080	0.892
Teachers	-0.4998*	0.0039	0
Media	-0.3807*	0.0074	0
Doctors	0.0217*	0.0039	0
Nurses	-0.4313*	0.0064	0
Protect	-0.2732*	0.0057	0
Food	-0.7077*	0.0051	0
Maintain	-0.7162*	0.0058	0
PersonalCare	-0.7574*	0.0071	0
Sales	-0.3593*	0.0037	0
OfficeAdmin	-0.3120*	0.0032	0
FamingFishing	-0.9619*	0.0108	0
Construction	-0.3398*	0.0044	0
Extraction	-0.4208*	0.0218	0
InstallMaint	-0.2248*	0.0044	0
Production	-0.3480*	0.0039	0
Transportation	-0.5340*	0.0044	0
Military	-0.3405*	0.0132	0
Black*BusinessOp	0.0574*	0.0180	0.001
Black*Financial	-0.0133	0.0185	0.47
Black*ComputerMath	0.1003*	0.0182	0
Black*Engineering	0.0851*	0.0225	0
Black*Science	0.0809*	0.0309	0.009
Black*Community	0.1503*	0.0157	0
Black*Legal	0.0293	0.0290	0.311
Black*Teachers	0.1363*	0.0130	0
Black*Media	0.1660*	0.0318	0
Black*Doctors	-0.0101	0.0150	0.501
Black*Protect	0.0426*	0.0161	0.008
Black*Food	-0.0220	0.0159	0.166
Black*Maintain	-0.0027	0.0167	0.873
Black*PersonalCare	0.0348	0.0191	0.068
Black*Sales	-0.1653*	0.0131	0
Black*OfficeAdmin	0.0543*	0.0099	0
Black*FamingFishing	0.0098	0.0546	0.858
Black*Construction	-0.1412*	0.0190	0
Black*Extraction	0.0021	0.1207	0.986
Black*InstallMaint	0.0787*	0.0176	0
Black*Production	-0.0284*	0.0130	0.029
Black*Transportation	0.0461*	0.0136	0.001
Black*Military	0.2702*	0.0363	0
Asian*BusinessOp	0.0067	0.0252	0.792

Asian*Financial	-0.0854*	0.0207	0
Asian*ComputerMath	0.0710*	0.0166	0
Asian*Engineering	0.0747*	0.0187	0
Asian*Science	-0.0689*	0.0246	0.005
Asian*Community	-0.0984*	0.0346	0.004
Asian*Legal	0.0119	0.0415	0.775
Asian*Teachers	-0.1085*	0.0210	0

Appendix C. Definitions of Occupational Variables

Variable	Occupation Definition
BusinessOp	Business Operations Specialists
Financial	Financial Specialists
ComputerMath	Computer and Mathematical Occupations
Engineering	Architecture and Engineering Occupations
Science	Life, Physical, and Social Science Occupations
Community	Community and Social Services Occupations
Legal	Legal Occupations
Teachers	Education, Training, and Library Occupations
Media	Arts, Design, Entertainment, Sports, and Media Occupations
Doctors	Healthcare Practitioners and Technical Occupations
Nurses	Healthcare Support Occupations
Protect	Protective Service Occupations
Food	Food Preparation and Serving Occupations
Maintaince	Building and Grounds Cleaning and Maintenance Occupations
PersonalCare	Personal Care and Service Occupations
Sales	Sales Occupations
OfficeAdmin	Office and Administrative Support Occupations
FamingFishing	Farming, Fishing, and Forestry Occupations
Construction	Construction Trades
Extraction	Extraction Workers
InstallMaint	Installation, Maintenance, and Repair Workers
Production	Production Occupations
Transportation	Transportation and Material Moving Occupations
Military	Military Personnel