Essays in Family Economics

Yu Kyung Koh

Submitted in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy
under the Executive Committee
of the Graduate School of Arts and Sciences

COLUMBIA UNIVERSITY

2023

Abstract

Essays in Family Economics

Yu Kyung Koh

This dissertation consists of three essays in family economics. The underlying objective of this dissertation is to better understand inequality in family formation and in intra-household allocation. The first two chapters study racial sorting in the United States marriage market. The third chapter studies the effects of higher female bargaining power on household consumption of married couples in the United States.

Chapter 1 studies the unequal gains from racial desegregation in the United States marriage market. Interracial marriages have increased in the United States over the past several decades, but the trends differ across race, gender, and education groups. This suggests that racial desegregation in the marriage market may not have equally improved the marriage prospects of different groups. This paper studies why some groups have gained more from marital desegregation than others over the past four decades. To this end, I build a transferable utility matching model to define and estimate the welfare gains from marital desegregation by comparing the equilibrium rates of singlehood in the observed marriage market with those in a completely segregated marriage market. I find that among Blacks and Whites, college-educated men gained more than their female and lower-educated male counterparts. To understand why, I implement a decomposition method to quantify how changing population and changing marital surplus have shaped the unequal gains, accounting for general equilibrium effects. I find that the rise in the welfare gains for

college-educated Black men is largely driven by the increase in the joint surplus from marriage with college-educated White women. Other Black men and women did not benefit as much from any change in the marital surplus, implying that race relations have not substantially improved in the marriage market except for the most educated Black men. I also find that the rise in welfare gains for college-educated White men is driven by the female-biased population increase among college graduates. Simulation results suggest that fixing the unbalance in marital surplus and making progress toward racial integration in the marriage market would significantly improve marriage outcomes for Black men and women.

Chapter 2 examines the geographical variation in racial sorting in the United States marriage market. There are substantial variations in interracial marriage rates across states, but it is challenging to disentangle the role of marital surplus from the population composition. I use a structural marriage market model to document the geographical variation and time trends in the racial assortativeness in marital matching across the US states. I document several new facts. First, preference for same-race marriage compared to different-race marriage is the highest in the southern states and the lowest in the western states, even after controlling for the demographic composition. Second, the ranking of each state in terms of racial assortative matching has been persistent over the past four decades. Third, the geographic variation in racial assortative matching is closely related to the racial attitudes of White respondents, but not of Black respondents. This suggests that geographic variation in racial assortative matching may be driven more by White people's marital preferences than by Black people's marital preferences. In terms of individual welfare gains from interracial marriage, I find that higher-educated Black men living in the West benefit more from interracial marriage and those living in the South do not benefit at all from interracial marriage. This is consistent with the geographical patterns in racial assortative matching. On the other hand, Black women do not benefit at all from interracial marriage regardless of where they live.

Chapter 3, which is joint work with So Yoon Ahn, studies how spousal bargaining power affects consumption patterns of married households in the US, using a detailed barcode-level dataset. While there has been substantial evidence from developing countries settings that bargaining power within the household affects household consumption, there is a lack of such evidence in more developed country settings like the US. To study this, we use two distribution factors as proxies for spousal bargaining power: spouses' relative education and spouses' relative potential wage, which is our preferred distribution factor. As an arguably exogenous measure of bargaining power, our relative potential wage is constructed as a Bartik-style measure of the female-to-male wage ratio, exploiting county-level variations in heterogeneous exposure to different industries and state-wide wage growth. We find that the expenditure shares on women's beauty goods increase and the expenditure shares on alcohol decrease significantly both when the relative education of wives increases and when the relative potential wages of wives increase. These results are consistent with household bargaining explanations. For couples with children, improved women's household bargaining position is associated with a higher budget share on books, stationery, and school supplies, which are potentially related to investment in children. Our evidence shows that local labor market condition that is favorable to women than men shifts household consumption towards more female-preferred goods among married couples in the US.

Table of Contents

Acknowledgments ix

Dedication xi

Chapter 1: The Unequal Gains from Racial Desegregation in the US Marriage Market . . . 1

1.1 Introduction 1

1.2 Motivating Trends 9

1.3 Data 12

1.4 Marriage Matching Model 14

1.4.1 The Setting 15

1.4.2 Identification of Marital Surplus and Expected Utility 17

1.4.3 The System of Equilibrium Matching Functions 19

1.4.4 Descriptive Statistics: Estimated Marital Surplus 20

1.5 Measuring Gains from Marital Desegregation 24

1.5.1 Estimation Strategy 25

1.5.2 Results 27

1.6 Decomposition 30

1.6.1 Overview of the Method 31

1.6.2 Decomposition Results 35

1.6.3 Discussion 43

1.7 Simulating Complete Racial Integration 43

1.8 Conclusion 47

Chapter 2: Geographical Variation in Racial Sorting in the US Marriage Market 49

2.1 Introduction 49

2.2 Data 53

2.2.1 US Census 53

2.2.2 General Social Survey 53

2.3 Assortative Matching Index 54

2.3.1 Application to the US context 56

2.4 Racial Assortative Matching Across US States 57

2.4.1 Geographical Variation in 2019 57

2.4.2 Persistence in Geographical Variation 60

2.4.3 Relations to Racial Attitude 62

2.5 Geographical Variations in Individual Gains from Interracial Marriage 64

2.6 Conclusion 68

Chapter 3: Spousal Bargaining Power and Consumption of Married Couples in the US: Evidence from Scanner Data 70

3.1 Introduction 70

3.2 Conceptual Framework 74

3.3 Data 76

3.3.1 Consumption 76

3.3.2 Industry Share and Wage 78

3.4 Descriptive Statistics 78

3.4.1 Gender Differences in Consumption: Singles Living Alone 78

3.4.2 Married Couple Sample 80

3.5 Spouse Relative Education and Married Couple's Consumption 83

3.6 Spouse Relative Potential Wage and Married Couple's Consumption 84

3.6.1 Construction of Gender Relative Potential Wage 84

3.6.2 Empirical Specification 86

3.7 The Impacts of Relative Wage on Household Consumption 87

3.7.1 Aggregate Goods I: Health and Beauty, Food, Alcohol, Tobacco 87

3.7.2 Aggregate Goods II: Non-Food Grocery and General Merchandise 91

3.7.3 Food Consumption Categories 93

3.8 Robustness 95

3.8.1 Alternative Channels 95

3.8.2 Placebo Checks Using Singles Living Alone 97

3.8.3 Rotemberg Weight 98

3.9 Structural Estimation: The Impacts of Relative Wages on Couples' Sharing Rule . . 99

3.10 Conclusion 104

References 106

Appendix A: Appendix to Chapter 1 112

A.1 Appendix: Tables and Figures 112

A.1.1 Additional Tables 112

A.1.2 Additional Figures 113

A.1.3 Sensitivity Check: Excluding Cohabiting Singles 115

A.2 Appendix: Decomposition 117

A.2.1 Full Solution of IFT Partials 117

A.2.2 Details on Decomposition Procedures 120

A.2.3 More decomposition results 124

Appendix B: Appendix to Chapter 2 128

B.1 Additional Tables 128

B.2 Additional Figures 129

Appendix C: Appendix to Chapter 3 132

C.1 Additional Figures 132

C.2 Additional Tables 136

C.2.1 Descriptive 136

C.2.2 Main Results: Relative Education 139

C.2.3 Main Results: Relative Potential Wages 142

C.2.4 Additional Results 148

C.2.5 Summary of Rotemberg Weight 149

C.3 Calculating the Rotemberg Weights 151

List of Figures

1.1 Interracial Marriage Rates Among Blacks and Whites 11

1.2 Female-to-Male Sex Ratio, Among 4-Year College Graduates, Age 35-44 12

1.3 Estimated Marital Surplus $\hat{\mathbf{Z}}_t$, 1980 vs 2019 21

1.4 Type-Specific Welfare Gains from Marital Desegregation 28

1.5 Details on the contributions from the changes in different-race, different-sex population 40

1.6 Marital Surplus Matrix in 2019, Actual vs. Complete Integration 45

1.7 Simulated Rate of Singlehood for Varying Degree of Racial Integration 46

2.1 Interracial Marriage, Among Married Black People, Age 35-50, 2019 50

2.2 Proportion Black Population, Age 35-50, 2019 50

2.3 Demeaned Racial Assortative Matching Index, Black-White, 2019 58

2.4 Racial Assortative Matching Index, Black-White, by Education, 2019 59

2.5 Racial Assortative Matching Index, Black-White, 1980 vs. 2019 61

2.6 Persistence in Racial Assortative Matching Over Time 62

2.7 Welfare Gains from Interracial Marriage, Black Men, 2019 66

2.8 Welfare Gains from Interracial Marriage, Black Women, 2019 67

3.1 Consumption Patterns by Single Women vs Single Men Living Alone, by Department 79

3.2 Mean Budget Shares by Gender, Singles and Couples Without Child 82

3.3 Effects of (Wife - Husband) Education on Household Budget Share 84

3.4 Results on Overall Consumption Budget Share, Aggregate I 88

3.5 Results on Overall Consumption Budget Share, Detailed Health and Beauty Aids . 90
3.6 Results on Overall Consumption Budget Share, Detailed Alcohol 91
3.7 Results on Overall Consumption Budget Share, Aggregate II 92
3.8 Results on Overall Consumption Budget Share, Aggregate II, By Child Status . . . 93
3.9 Results on Food Budget Share 95

A.1 Interracial Marriage Rate, Among Married, Age 35-44 113
A.2 Interracial/Interethnic Marriage For Each Race/Ethnicity, Among Married, Age 35-44 114
A.3 Changes in Marital Surplus Z^{IJ} from 1980 to 2019 115
A.4 Type-Specific Welfare Gains from Marital Desegregation, Excluding Cohabiting Singles 116
A.5 Contribution of Each Population Primitive to the 1980-2019 Change in the Welfare Gains, For White CG Men and White CG Women 125
A.6 Contribution of Each Marital Surplus Primitive to the 1980-2019 Change in the Welfare Gains, For White CG Women and White HSG Women 126
A.7 Contribution of Each Marital Surplus Primitive to the 1980-2019 Change in the Welfare Gains, For White CG 127

B.1 Marriage Rate by Race and Gender, 2019 129
B.2 Welfare Gains from Interracial Marriage, Black Men, 1980 130
B.3 Welfare Gains from Interracial Marriage, Black Women, 1980 131

C.1 Mean Budget Shares by Gender, Singles Living Alone 132
C.2 Singles vs. Couples 133
C.3 Consumption Patterns by Single Women vs Single Men without Children, Detailed Alcohol 134
C.4 Raw Budget Share by Gender, Single Without Child 135
C.5 Distribution of (Wife - Husband) Years of Education 135

List of Tables

1.1 Selected Marital Surplus Involving White Spouse 22
1.2 Selected Marital Surplus Involving Black Spouse 23
1.3 Data vs. IFT: 1980-2019 Changes in Welfare Gains from Marital Desegregation . . 35
1.4 Decomposition of the 1980-2019 Changes in the Welfare Gain from Marital Desegregation 36
1.5 Decomposition: Top three contribution from changes in **Z**, Black CG Men 37
1.6 Decomposition: Top three contribution from changes in **Z**, Black CG Women . . . 39
1.7 Contributions from population changes to welfare gains for White CG men 40
1.8 Decomposition: Top three contributions from **Z**, White HSG Men 41
1.9 Contributions from population changes to welfare gains for White CG women . . . 42

2.1 Racial Sentiments Across Census Regions 63

3.1 Statistics on Total Annual Expenditure, Married Couples 81
3.2 Effect of Gender Wage Ratio on Household Outcomes 96
3.3 Effect of Respective Gender Wage on Budget Share (%), Singles Living Alone . . . 98
3.4 Impacts of Gender Wage Ratio on Sharing Rule of Married Couples 104

A.1 Percentage of Other Race and Mixed Races in Each Census Year, Female Aged 35-44, Male Aged 37-46 112
A.2 Percentage of Never Married Singles who Cohabit in Each Census Year, Female Aged 35-44, Male Aged 37-46 113

A.3 Decomposition: Top three contribution from changes in **Z**, Black HSG Men 124
A.4 Decomposition: Top three contribution from changes in **Z**, Black HSG Women . . 124

B.1 Definition of Census Regions 128

C.1 Description of Nielsen Departments 136
C.2 Demographic Characteristics of Married Couples 137
C.3 Industry Composition by Gender (%) 138
C.4 Effect of (Wife-Husband) Years of Education Conditional on Husband's Education on Budget Share (%), (Aggregate I) 139
C.5 Effect of (Wife-Husband) Years of Education on Budget Share (%), (Aggregate I) . 139
C.6 Effect of (Wife-Husband) Years of Education Conditional on Husband's Education on Budget Share (%), (Aggregate II) 140
C.7 Effect of (Wife-Husband) Years of Education on Budget Share (%), (Aggregate II) . 141
C.8 Effect of Gender Wage Ratio on Budget Share (%), (Aggregate I) 142
C.9 Effect of Respective Gender Wage on Budget Share (%), (Aggregate I) 142
C.10 Effect of Gender Wage Ratio on Budget Share (%) (Aggregate II) 143
C.11 Effect of Respective Gender Wage on Budget Share (%) (Aggregate II) 144
C.12 Effect of Gender Wage Ratio on Food Budget Share (%) 145
C.13 Effect of Wage by Gender on Food Budget Share (%) 145
C.14 Effect of Gender Wage Ratio on Detailed Health and Beauty (%) 146
C.15 Effect of Wage by Gender on Detailed Health and Beauty (%) 147
C.16 Effect of Respective Gender Wage on Budget Share (%), Singles Living Alone . . . 148
C.17 Summary of Rotemberg Weight for Female Potential Wage 149
C.18 Summary of Rotemberg Weight for Male Potential Wage 150

Acknowledgements

I am deeply indebted to my advisors, Pierre-André Chiappori and Bernard Salanié, for their continuous guidance, patience, and support. It was only after taking Pierre-André's wonderful family economics course during my third year of graduate studies that I decided to pursue research in family economics. Pierre-André inspired me to study families to better understand economic inequality, and he taught me how economic tools can be used to study important topics related to families. His profound knowledge, insight, and extraordinary clarity always helped me better comprehend puzzles that I frequently encountered while doing research. Bernard always shared incredible insight on everything we discussed, and he never failed to help me find better directions whenever I was stuck. He spent an enormous amount of time on my work, always giving me thorough advice that substantially improved each and every part of my papers. I learned the importance of rigor and perseverance from him. Discussions with Pierre-André and Bernard were crucial in every stage of my dissertation, from shaping ideas to navigating complex issues to finishing my papers. I was incredibly lucky to have them as my advisors.

I am extremely grateful to Brendan O'Flaherty, who taught me how to study racial issues as an economist. Dan always shared his extensive and deep knowledge and insight in this area, helping me identify and better understand the economic problems related to race. Discussions with him were tremendously beneficial in developing the first and second chapters of my dissertation. I am also very grateful to Sandra Black and Rodrigo Soares for their valuable and thoughtful feedback all the time and for serving on my dissertation committee. I also thank the participants at the Applied Micro Theory Colloquium and the Applied Micro Method Colloquium who witnessed my projects, including the failed ones, from their immature stages. Their constructive feedback during each of my presentations immensely helped me make progress. These weekly colloquia also gave me invaluable learning experiences by letting me witness how each student's projects beautifully develop over the years.

So Yoon Ahn is the best co-author I could ever ask for. Collaborating with So Yoon in writing my third chapter has always been a great joy. As a former Columbia student and now a promising young economist, she has been an excellent example and mentor to me. I learned so much from her by working together, and she helped me further develop my research skills and grow as a researcher. I look forward to further collaborating in the years to come.

I must also thank Amy Devine and Rosie Lourentzatos for always being incredibly helpful with the administrative work, especially during the hectic job market. I am also grateful to Kwanjeong Education Foundation for its generous financial support throughout my doctoral studies.

My colleagues and friends at Columbia were a crucial part of my Ph.D. journey. I would like to express special gratitude to Amanda Awadey and Shruti Mishra, for being amazing friends ever since the math camp and for giving me the strength to move forward with this dissertation even during difficult times. I would also like to extend my sincere thanks to all my friends who constantly gave me personal and professional support and filled my Ph.D. with cherishable memories: Anastasia Burya, Martsella Davitaya, Sakshi Gupta, Yoon Joo Jo, Paul Sungwook Koh, Suanna Oh, BooKang Seol, Yeji Sung, Ken Teoh, Krzysztof Zaremba, and many others.

I am extremely thankful to Han for always being by my side through all the highs and lows of this journey.

I am most grateful to my family for their unconditional love and support. My parents, my sister, and my grandparents provided me with tremendous care and support in every chapter of my life. They motivated me to dream bigger and work harder. Without them, I would not be where I am today.

Dedication

To my family,

for their unconditional love and support

Chapter 1: The Unequal Gains from Racial Desegregation in the US Marriage Market

1.1 Introduction

Interracial marriage has been slowly but steadily increasing in the US since the *Loving v. Virginia* decision in 1967, which lifted all legal barriers to marrying across racial lines.[1] However, the trends are not the same for everyone. Among Blacks and non-Hispanic Whites (henceforth, Whites), men with four-year college degree (henceforth, college-educated) are more likely to marry out of their racial group than their female counterparts and their lower-educated male counterparts. This suggests that interracial marriage may not have equally improved everyone's marriage prospect.[2]

Interracial marriage matters, because not only is it a barometer of social integration by itself, but it also has a potential to transmit positive racial attitude to children.[3] Moreover, interracial marriage opens up more options of partners, which is likely to be beneficial for marriage prospects. However, if some groups face disproportionately high barriers to marrying out, it would limit their pool of potential partners. This is particularly concerning for Black women, who have a lack of marriageable men within their race due to the high incarceration rate of Black men (Charles and Luoh, 2010; Liu, 2020; Caucutt, Guner, and Rauh, 2021). Therefore, understanding the disparities in interracial marriage rates is important to identify the barriers each group faces in the marriage

[1] As shown in Figure A.1, the interracial marriage rate among married people aged 35-44 increased from 3% in 1980 to 11% in 2019.

[2] For example, although increasingly more Black women are marrying out of their race, *even more* Black men are marrying out. Therefore, it is unclear if Black women have better marriage prospects in the desegregated marriage market.

[3] Prior evidence shows that children of interracial couples have more social contact with racially diverse groups (Kalmijn, 2010) and are less likely to identify with an ancestry (Duncan and Trejo, 2011).

market that limit their marriage prospects.

In this paper, I address three main questions. First, who gained more from the option of interracial marriage (which I call “marital desegregation"[4]) in the US marriage market over the past four decades? Second, why did some groups gain more than others? Third, how would the rates of singlehood change if the marriage market becomes more racially integrated? This paper provides quantitative assessments of these questions by estimating a structural marriage market model.

Marriage rates are determined by *both* marital preferences *and* population distribution. Hence, it is challenging to investigate the role of changing marital preferences and changing population from the marriage rates alone. On the one hand, interracial marriage rates may differ across groups due to differing marital preferences, which can be shaped by social acceptance in case of interracial marriage. Prior evidence reveals some explanations that are consistent with the interracial marriage trends. For example, women have stronger same-race preferences in dating than men (Fisman et al., 2008); higher educated people are more open to interracial marriage (Livingston and Brown, 2017); and Black women experience more social pressures and discrimination in marrying out than Black men do (Banks, 2012; Stewart, 2020). On the other hand, population supplies can also affect interracial marriage patterns, independent of preferences. For example, there has been a reversal of the gender gap in college education in the US (Goldin, Katz, and Kuziemko, 2006; Chiappori, Iyigun, and Weiss, 2009), resulting in a larger number of college-educated women than college-educated men across all races. Because of this trend, it may be that college-educated White and Black men marry out more because there are now more college-educated potential partners in the marriage market. Without a clear framework, it is difficult to distinguish which factor – i.e. population distribution or marital preferences – plays a larger role in driving the interracial marriage rate of each group.

I address these challenges by building a transferable utility matching model in the spirit of Choo and Siow (2006). The matching model disentangles marital preferences from the observed

[4]The term “desegregation" refers to the ending of the separation of two groups, usually referring to races. Hence, marital desegregation refers to the state with no *legal* barriers to interracial marriage. Note that social or cultural barriers to interracial marriage can exist in the desegregated marriage market.

marriage patterns. In the model, marital preferences are captured in *marital surplus*, which is the excess of the sum of utilities a couple gets when married together over what they get when remaining single. The notion of marital surplus can contain any economic or non-economic benefits from each type of marriage, relative to singlehood. Marital surplus reflects both husband's and wife's marital preference for each marriage. In case of interracial marriage, marital surplus reflects the level of social stigma or preferences attached to each type of interracial marriage.

Moreover, the matching model allows me to quantify the roles of changing population and changing marital preferences in shaping differing interracial marriage patterns, as well as individual's marriage prospects. This is because the matching model provides a clear link between the equilibrium marriage patterns and the marital surplus as well as the population distribution. It is important to note that any change in population or in marital surplus affects marriage patterns for *all* men and women, thereby having equilibrium consequences.[5] The model is useful in capturing the general equilibrium effects of various changes in population and marital preferences that took place in the US marriage market over the past four decades. This feature allows me to identify specifically which changes in population and in marital surplus played the largest role in the interracial marriage patterns and welfare of each group.

To answer the research questions, I use the following procedures. First, using the matching model estimated with the US Census data, I measure the welfare gains from marital desegregation by comparing the expected utilities in the (actual) desegregated marriage market and the expected utilities in the (counterfactual) completely segregated marriage market. This measure captures how much additional welfare each group has gained from the option of interracial marriage, relative to the case with no such option. Welfare gain is fully summarized by better chances of getting married. Second, to understand why welfare gains differ across groups, I implement a decomposition method to measure the contributions made by changes in the population distribution and changes in the marital surplus from all types of race-education pairs. Lastly, I perform a counterfactual

[5]For example, Ahn (2022) shows that the changes in the cost of cross-border marriage between Taiwan and Vietnam, which were driven by the visa policy and the emergence of matchmaking firms, affected overall marriage patterns and intra-household allocations of *all* men and women.

simulation to predict how progress towards complete racial integration would affect the marriage rates across groups. I define *complete racial integration* in the marriage market as a scenario where race is no longer a factor considered for marriage decision – i.e. there is no cost of marrying across racial lines. I focus on explaining the gains for Blacks and Whites in this paper, because these two races have experienced the largest increases in interracial marriage rates over the past four decades.[6]

I begin my analysis by estimating the matching model. To flexibly allow marital surplus to differ across race and education, I specify the type space used for matching as four major races/ethnicities (White, Black, Hispanic[7], Asian) interacted with four levels of educational attainment. I estimate the model for each year using the Census data from 1980 to 2019. The estimated marital surplus matrices show several notable patterns. First, the joint surplus from interracial marriage increased over time only for college-educated pairs, not for non-college-educated pairs. This reveals that the cost of interracial marriage have substantially declined for higher educated groups. Second, the joint surplus from interracial marriage varies widely with the gender and race of the spouse: Black-White marriages exhibit the lowest joint surplus among the interracial marriages involving a White spouse; among Black-White marriages, marriages involving Black women have the lowest joint surplus; and the joint surpluses from interracial marriage among minority groups are lower than the joint surpluses from interracial marriage involving a White spouse. These results confirm that there is a wide variation in the preferences or social stigma attached to each type of interracial marriage.

Next, I characterize the welfare gains from marital desegregation using the matching model.

---

[6]The reasons I do not focus on explaining the gains for Hispanics and Asians are two-fold: First, interracial marriage rates have been fairly high (over 15%) for them even in 1980, and their propensities of marrying out did not increase over time as much as those of Blacks and Whites, as shown in Figure A.2. Second, it is important to distinguish Hispanics and Asians by immigration status, as different generations of immigrants may have systematically different preferences for same-race marriage (Lichter, Carmalt, and Qian, 2011; Furtado, 2015). It is outside the scope of this paper to examine welfare gains for Hispanics and Asians who exhibit markedly different interracial marriage trends and immigration trends from Blacks and Whites.

[7]Hispanic is an *ethnicity*, which is a social group that shares a common and distinctive culture, religion, and/or language. While ethnicity and race are not exactly the same terms, this distinction can be subject to debate (Lopez, Krogstad, and Passel, 2022). For simplicity, I refer to interracial/interethnic marriages as “interracial marriage" throughout this paper.

These gains are defined as the expected utilities in the observed marriage market (with option of interracial marriage) minus the expected utilities in the counterfactual marriage market (with no option of interracial marriage) for each year. In the completely segregated market, everything else is the same as the observed world, *except* that the costs to interracial marriage are set to be infinitely high for everyone. The counterfactual marriage patterns are constructed by setting the marital surpluses for all interracial marriages as infinitely negative and computing new equilibrium sorting patterns. Under the distributional assumption of Gumbel-distributed random preferences, the expected utilities in the framework are fully summarized by the probabilities of singlehood for each type. Hence, the welfare gains from marital racial integration essentially compare the observed rates of singlehood with the equilibrium rates of singlehood in a complete segregation scenario.

I find that among Black people, marital racial desegregation has improved the welfare of college-educated Black men the most. This means that college-educated Black men's chances of getting married became substantially higher due to interracial marriage. Even as early as 1980, college-educated Black men received positive welfare gains from marital desegregation, while their female counterparts and their lower-educated male counterparts received zero or negative gains. Over time, college-educated Black men have experienced a sharper increase in welfare gains than any other group among Blacks. In 2019, the magnitude of the welfare gains for college-educated Black men is substantial: marital desegregation has reduced the probability of being single for college-educated Black men by 17.5% compared to a complete segregation scenario.

In contrast, Black women have not gained at all from marital racial desegregation, regardless of their education level, across all years. This means that the option of interracial marriage did *not* improve Black women's chances of getting married at all, despite the fact that there are a larger pool of potential partners. This reveals that part of the reason behind the low marriage rate of Black women[8] is that they do not benefit at all from the option of marrying out.

[8]As discussed in Caucutt, Guner, and Rauh (2021), only 32% of Black women aged 25-54 were currently married in 2018, which is much lower than the marriage rate of White women (62%).

Among White men, only college-educated men have experienced an increase in welfare gains over time, while non-college-educated men did not experience any rise in the gains. In 2019, the welfare gains for college-educated White men are translated into a reduction in the probability of being single by 8% compared to the scenario with complete segregation, while the corresponding reduction is 2% for high school graduate White men. In contrast, all White women experienced similar rises in welfare gains over time, regardless of their education levels, from almost zero welfare gains in 1980. Overall, marital racial desegregation is welfare-improving for all White women in 2019; the probability of being single for White women is reduced by $3 \sim 5\%$ compared to a complete segregation scenario.

To understand why some groups gained more than others, I implement a decomposition method, for the first time in the marriage literature, to quantify the roles of various market-level changes, which include changing population and changing marital preferences. The key idea for this method is to apply the implicit function theorem to a system of equilibrium matching functions. This captures the general equilibrium effects of each market-level change on the welfare gains from marital desegregation for each type of man and woman. I use a fine-tuning method to link the four decades of gradual changes in marital surplus and in population distribution to the changes in welfare gains. The estimated changes in welfare gains from this method closely match the changes from the data, thereby confirming the validity of this method. The main benefit of this method is that it successfully summarizes a large number of effects from changing population and changing marital preferences.

I find that the population changes and the marital surplus changes made different impacts across groups. The rise in the college-educated Black men's welfare gains is largely driven by the increase in the joint surplus from the marriage with college-educated White women. Other Black men and women did not benefit as much from any change in the marital surplus. Notably, while college-educated Black women also gained from the increase in the joint surplus from the marriage with college-educated White men, this gain is not as large as what college-educated Black men gained from marrying White women. College-educated Black women's gain is also partly canceled out by other negative forces, such as the increase in marital surplus for marriage between Black men and White women. This finding suggests that unbalanced marital preferences, meaning that there are higher marital surplus for (Black men, White women) marriage than (White men, Black women) marriage, led to the unequal gains from marital desegregation among Black people.

For Whites, I find that the rise in the welfare gains for college-educated White men is driven by the rise in the number of college-educated Asian and Hispanic women. This shows that the increase in interracial marriage for college-educated White men is a byproduct of the population changes, rather than the consequence from the increase in the gains from interracial marriage. College-educated White women had negative effects from the population changes, which reflects that the imbalanced sex ratio among the college graduates, generated by the reversal of the college gender gap (Goldin, Katz, and Kuziemko, 2006), played an important role in driving the gender difference in welfare gains among White college graduates.

A key takeaway from the decomposition analyses is that not everyone benefits from interracial marriage, despite having a larger pool of potential partners, if there is an unbalanced sex ratio or a gender disparity in marital preferences for interracial marriage. For example, one of the key findings is that Black men's interracial marriage has persistently higher marital surplus than Black women's interracial marriage. This gender gap has led to zero welfare gains for Black women from marital desegregation, because Black women face a limited marriage pool from both within their race (because more Black men are marrying out) and across races (because Black women do not interracially marry as much). This has implications for family formation not just in the US setting, but also in other countries where population is becoming more racially diverse and different groups may face different barriers to interracial marriage.

Finally, I perform the counterfactual simulation to predict how the marriage rates for different groups would change if the racial boundaries diminish and there is more social acceptance toward interracial marriages. To this end, I construct a counterfactual marital surplus for *complete racial integration* so that it only depends on education of both spouses. This is constructed as a weighted average for each education pair based on the estimated marital surplus from data. I then construct a gradual path from the current state to the complete integration state and compute new equilibrium marriage patterns for each point along the path. The simulation for the survey year 2019 predicts that progress towards complete racial integration would significantly reduce the single rates of Black men and women. In contrast, racial integration would not affect the single rates of White men and women at all stages. This suggests that the efforts toward improving racial relations could enhance the marriage prospects for Black people, who currently have low marriage rates and a high prevalence of single mothers, without harming the marriage prospects for White people.

This paper contributes to several strands of literature. First, I contribute to the literature on the evolution of interracial marriage in the US. Existing literature examines interracial marriage trends across group using descriptive statistics and provides qualitative discussions (Fryer Jr., 2007; Livingston and Brown, 2017). I provide the first quantitative assessments of what drives the heterogeneous interracial marriage rates, by structurally estimating the effects from various market-level changes in population and marital surplus. Moreover, several existing studies have investigated the evolution of interracial marriage by developing measures of racial endogamy[9] (Fu and Heaton, 2008; Qian and Lichter, 2011). However, these measures do not capture which specific group of men or women benefited from the changing overall tendencies to marry within one's race. I provide the first estimates on who gained more from marital desegregation and by how much.

This paper also contributes to the literature on equilibrium marriage sorting that uses a frictionless transferable utility (TU) framework. This paper is one of a few studies that investigate racial sorting using this framework. Since Choo and Siow (2006) provided a benchmark model for empirically implementing the frictionless TU matching model with unobserved characteristics, this framework has been used and extended to study marriage sorting on various dimensions, including education (Chiappori, Salanié, and Weiss, 2017; Chiappori, Costa Dias, and Meghir, 2020), personality traits (Dupuy and Galichon, 2014), and income (Chiappori et al., 2022). Related to my paper, there has been a growing literature on interracial/interethnic marriages, including Ciscato and Weber (2020), who study the changes in multi-dimensional sorting in the US; Anderberg and

[9]The term "racial endogamy" refers to the tendency of people to choose mates who are in the same racial group.

Vickery (2021), who study the role of group density on racial sorting in the UK; and Adda, Pinotti, and Tura (2022), who study the role of legal status and cultural distance on intermarriage in Italy. However, none of these papers examines who gained from desegregation in the US marriage market, and my paper is the first to define and estimate the welfare gain from marital desegregation for each demographic group. Furthermore, this paper is the first to decompose the changes in equilibrium matching patterns into contributions by various market-level changes using the TU matching model.

Lastly, I add to the literature on the causes of the diverging patterns in marriage. As reviewed in Lundberg, Pollak, and Stearns (2016), marriage rates in the US have declined faster for high school graduates than college graduates and for Blacks than Whites. Most of the existing studies have examined the causes *within* each race, such as the rising incarceration of Black men (Charles and Luoh, 2010; Liu, 2020; Caucutt, Guner, and Rauh, 2021) and the decline in employment prospects for low-skilled male workers (Autor, Dorn, and Hanson, 2019). I add to this literature by studying how different barriers to marrying *across* racial lines affect the probability of singlehood for different demographic groups.

The rest of the paper is organized as follows. Section 1.2 documents motivating trends that highlight difficulties in interpreting the interracial marriage patterns. Section 3.3 describes the data and the sample selection for model estimation. Section 1.4 presents the matching model and explains the estimation of the marital surplus and expected utilities. Section 1.5 explains the method to measure the welfare gains from marital racial desegregation and presents the results. Section 1.6 presents the decomposition method and the results. Section 1.7 performs counterfactual simulations for complete racial integration. Section 2.6 concludes.

1.2 Motivating Trends

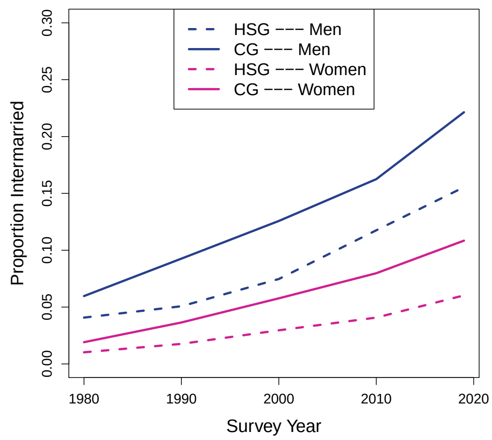
Interracial marriage rates have not increased in the same way across gender and education groups. Figure 1.1a shows that Black men with four-year college degree are more likely to marry out than their female counterparts and their high school graduate male counterparts. Notably, even high school graduate Black men are more likely to marry out than college-educated Black women. Similarly, Figure 1.1b shows that college-educated White men marry out more than their lower-educated male counterparts and their female counterparts.

These differing trends reveal that the interracial marriage may not have benefited everyone. For example, while Black women increasingly marry out more over time, Black men, especially the most educated ones, marry out even more. Therefore, it is unclear whether interracial marriage improved Black women's chances of marriage by giving them more options of partners or whether it worsened their chances by increasing competition for the college-educated Black men. Similar reasoning holds for White women, who marry out less than college-educated White men. This motivates the need for a formal measure of the welfare gain each group receives from marital desegregation, which I construct in Section 1.5.

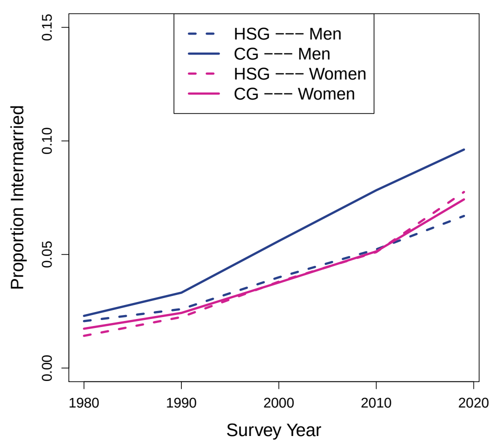
It is also difficult to understand what drives these differing propensities of marrying out across groups. As emphasized throughout the literature on marriage markets (Chiappori and Salanié, 2016; Schwartz, 2013), marriage rates capture both the gains from marriage and the population distribution, and it is not straightforward to distinguish the two from marriage rates alone. Several changes in the US population may have affected interracial marriage rates, independent from the changes in the preferences or social stigma attached to interracial marriage. First, the US population has become more racially diverse due to the rise in Hispanic and Asian immigrants. Hispanic population has increased fourfold and Asian population has increased over sixfold since 1980 (Flores, 2017; Budiman and Ruiz, 2021). Therefore, the rise in interracial marriage could be a mechanical consequence of the rising Hispanic and Asian population.

Second, there has been a reversal of the gender gap in college education: while more men used to have college degree than women in the past, the opposite is true now. This is a well-documented trend (Goldin, Katz, and Kuziemko, 2006; Chiappori, Iyigun, and Weiss, 2009; Chuan and Zhang, 2022). What I additionally show in Figure 1.2 is that this reversal in the gender gap is true for *all races*. This implies that there are now a larger number of potential college-educated partners, across all races, for men than for women among college graduates. Therefore, the gender

Figure 1.1: Interracial Marriage Rates Among Blacks and Whites



(a) Blacks

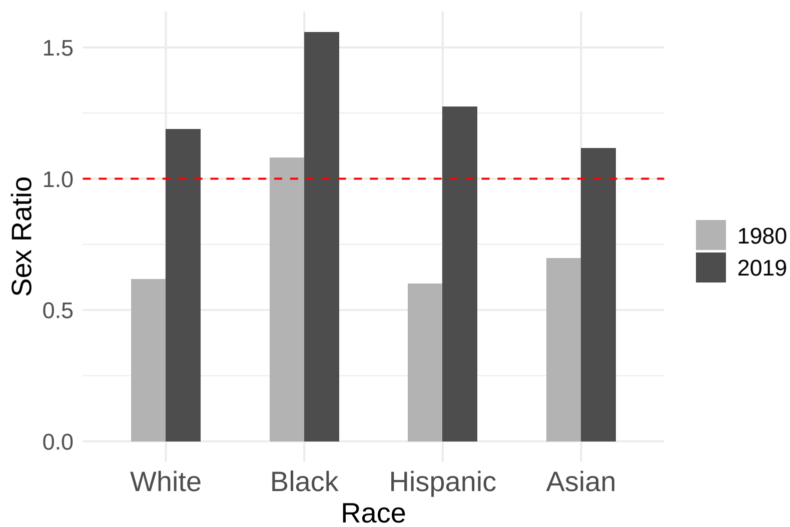


(b) Whites

Note: This figure shows the proportion of those who married out of their race among married individuals of the specified group aged 35-44 in each survey year. “HSG" refers to high school graduation or the equivalent GED. “CG" refers to the four-year college degree or above. Data sources for this figure are: 1980 5% sample Census, 1990 5% sample Census, 2000 5% sample Census, 2010 5% sample American Community Survey (2006-2010 5 year pooled sample), 2019 5% sample American Community Survey (2005-2019 5 year pooled sample). Survey weight is applied.

differences in interracial marriage shown in Figure 1.1 could be the mechanical consequence from the reversal of the gender gap in higher education, rather than the consequence from the gender differences in the gains from interracial marriage. Without a model, it is not possible to disentangle the role of the changes in the gains from interracial marriage from the role of population changes in driving the interracial marriage rates.

Figure 1.2: Female-to-Male Sex Ratio, Among 4-Year College Graduates, Age 35-44



Note: This figure shows sex ratio (female-to-male) among college graduates aged 35-44 for each race in 1980 and in 2019, respectively. Data sources for this figure are: 1980 5% sample Census microdata and 2019 5% sample American Community Survey (2015-2019 5-year pooled sample). Survey weight is applied.

Motivated by these conjectures, I proceed by building a structural matching model in Section 1.4 that provides a clear framework to (i) measure the welfare gains from marital desegregation and to (ii) disentangle the effects of the structural marital gains from the mechanical effects of the population distribution.

1.3 Data

I begin by describing the data used for estimating the marriage matching model for each year spanning from 1980 to 2019. I use the US Decennial Census for years 1980, 1990, and 2000, and I use the 5-Year American Community Survey sample for the years 2010 and 2019, all of which are extracted from IPUMS (Ruggles et al., 2022).[10] The reason I start from year 1980 is because the census question on the Hispanic origin was added in 1980.[11] For the previous years, the Hispanic origin of each respondent is imputed by the IPUMS based on several criteria including one's and family's birthplace, surname, and family relationship, among others. However, it is problematic to use the imputed Hispanic variable, because interracial/interethnic marriages involving Hispanics are not well-identified.[12]

I impose the following sample restriction for estimation. For *each* survey year, I first select the sample of currently married couples where wife is aged 35-44 and husband is aged 37-46. The lower bound of this age range is selected to exclude the ages that are too young so that people can marry in the future. The upper bound of the age range is selected to keep the age distribution across different calendar years comparable.[13] Two years of age gap between husband's age group and wife's age group reflects the fact that men tend to marry younger women, and the most common spousal age differences in the data are 1 and 2 years.[14] I focus on heterosexual married couples, because same-sex marriage had not been legalized nationwide until 2015.

To the married couple sample, I add the sample of never-married single men and women who are in the same corresponding age groups. I do not include divorced people in the single sample to abstract away from the issues of selection into divorce. Institutionalized individuals are excluded from the estimation sample, as they are unlikely to be participating in the marriage market. Never-

[10]All data are 5-in-100 national sample of the population for the corresponding year.

[11]In fact, as discussed in O'Flaherty (2015), "Hispanic" only gained meaning around 1970 in the US.

[12] Specifically, the occurrences of marriages between non-Hispanic whites and Hispanics are recorded to be zero in 1960 and 1970. This is because spouse's race is one of the criteria to impute the Hispanic origin of individuals for 1960 and 1970 Decennial Censuses.

[13]The choice of age range 35-44 is common in the marriage literature (e.g. Chiappori, Costa Dias, and Meghir (2020), Bertrand et al. (2021)).

[14]Note that this age restriction rules out couples who have spouses outside the specified age range. For example, age 35 women married to age 33 men are excluded from the sample. This age restriction is necessary to properly estimate the marital surplus and perform counterfactual analyses, but it may be problematic as it arbitrarily rules out certain age pairs.

married singles in the estimation sample include those living with unmarried partners.[15] As shown in the Table A.2, cohabitation among the sample of singles has increased from 11.3% in 1980 to 24.6% in 2019. I later perform sensitivity checks in Appendix A.1.3 and confirm that excluding cohabiting singles do not affect the main results.

I now describe the type spaces used for the estimation. I consider 4 races/ethnicities in my estimation, which are Non-Hispanic Whites, Black/African Americans, Hispanics, and Asians.[16] Hence, the type space for race/ethnicity is $\mathcal{R} \equiv \{White, Black, Hispanic, Asian\}$. I exclude other races, including mixed races because their sample size is too small; Appendix Table A.1 shows that other races, which include Native Americans, Alaska Indians, and other races, are less than 1% of the population of interest each year; and people who reported to be mixed race, an option available from 2000 onward, make up less than 3% for each available year. For education type space, I consider four levels of educational attainment: $\mathcal{E} \equiv \{HSD, HSG, SC, CG\}$, where HSD: high school dropout, HSG: high school graduate or GED with no college education, SC: less than 4 years of college education, and CG: 4 years of college education or more. Hence, the full type spaces for the estimation are $\mathcal{R} \times \mathcal{E}$, which consist of 16 different types. Specifically, $\mathcal{R} \times \mathcal{E} = \{WhiteHSD, WhiteHSG, WhiteSC, WhiteCG, \ldots, AsianHSD, AsianHSG, AsianSC, AsianCG\}$.

1.4 Marriage Matching Model

In this section, I present the matching model that serves as the building block for the analyses of interracial marriage throughout this paper. Building on Choo and Siow (2006), I construct a frictionless matching framework with perfectly transferable utility (TU) and random preferences to identify and estimate the structural gains from any race-education matching in the US marriage market.

[15]From 1990 Census and onwards, “unmarried partner" living with the head of household can be identified.

[16]“Asian" include Chinese, Japanese, and other Asians or pacific islanders.

1.4.1 The Setting

In this setting, each man or woman has two traits that are observed by the analyst: race and education.[17] Each man i belongs to a type $I = (R_i, E_i) \in \mathcal{M} \equiv \mathcal{R} \times \mathcal{E}$, where $\mathcal{R}$ and $\mathcal{E}$ denote the type spaces for race and for education, respectively. Similarly, each woman j belongs to a type $J = (R_j, E_j) \in \mathcal{F} \equiv \mathcal{R} \times \mathcal{E}$. In addition, each individual has other traits that are unobservable to the analyst but are observable to all men and women.[18]

A *matching* indicates who marries whom, including the option of singlehood. I augment the type spaces for men and women to allow for singlehood: $\tilde{\mathcal{M}} := \mathcal{M} \cup \{\emptyset\}$ and $\tilde{\mathcal{F}} := \mathcal{F} \cup \{\emptyset\}$, where $\{\emptyset\}$ means no partner. Feasible matching must satisfy the population constraints. I denote n^I the number of type I men and m^J the number of type J women available in the marriage market. I also let μ^{IJ} denote the number of (I, J) marriages, $\mu^{I\emptyset}$ the number of single I men, $\mu^{\emptyset J}$ the number of single J women. The feasibility condition is the following:

$$n^I = \mu^{I\emptyset} + \sum_J \mu^{IJ} \quad \forall\ I \tag{1.1}$$

$$m^J = \mu^{\emptyset J} + \sum_I \mu^{IJ} \quad \forall\ J \tag{1.2}$$

In other words, the sum of the number of married and single must be equal to the total number of individuals in the marriage market by type and gender.

In a perfectly transferable utility framework, a matching also indicates how marital surplus z_{ij} generated by (i, j) marriage is divided between the couple. The joint marital surplus is interpreted as the total utilities man i and woman j get when married together minus the sum of utilities man i and woman j get when remaining single. In other words, marital surplus captures couple-specific

[17] I only focus on these two traits as they are likely to be determined before marriage. Other observable characteristics from the census data, such as the current wage and hours of work, are not used because they can be the outcomes that are endogenously determined by marriage.

[18] The unobservable heterogeneity allows for richer matching patterns, which is otherwise not possible with a deterministic matching model. As discussed throughout the matching literature (Chiappori and Salanié, 2016; Chiappori, 2017; Galichon and Salanié, 2022), the uni-dimensional deterministic matching model gives a stark prediction that matching is perfectly assortative, which is obviously unrealistic in the real world.

economic and non-economic gains generated by marriage, *relative to* singlehood.[19] Marital surplus reflects both husband's and wife's preferences for each marriage. It is expressed as a sum of two components:

$$z_{ij} = Z^{IJ} + \varepsilon_{ij} \tag{1.3}$$

where Z^{IJ} is a deterministic part of the surplus that depends only on observed types of spouses, and ε_{ij} is an idiosyncratic part of the surplus that reflects unobserved heterogeneity in marital preferences. When Mr. i and Ms. j marry each other, the joint surplus z_{ij} is divided between them. This is expressed as $z_{ij} = u_i + v_j$, where u_i is the payoff for Mr. i and v_j is the payoff for Ms. j. While marital surplus is a model primitive, how it is divided between the couple is determined by marriage market equilibrium.

Similarly, the utility of singles is expressed as:

$$z_{i\emptyset} = Z^{I\emptyset} + \varepsilon_{i\emptyset}$$
$$z_{\emptyset j} = Z^{\emptyset J} + \varepsilon_{\emptyset j}$$

where $Z^{I\emptyset}$ and $Z^{\emptyset J}$ are normalized to zero.

A matching equilibrium is achieved when (i) no Mr. i or Ms. j who is currently married would rather be single and (ii) no Mr. i or Ms. j who are not currently married together would both rather be married together than remain in their current situation. This equilibrium condition results from stability, and the stable matching is generally unique (Gale and Shapley, 1962; Shapley and Shubik, 1971).

[19]The relative nature of the marital surplus is important, because the analyst cannot separately identify the utilities from marriage and the utilities from singlehood, from the marriage patterns alone. It is only possible to identify the relative utilities that a couple gets, *relative to* singlehood, from the marriage patterns.

1.4.2 Identification of Marital Surplus and Expected Utility

One of the main goals of this model is to recover the marital surplus (Equation (1.3)) from the observed marriage patterns. As discussed in Choo and Siow (2006) and Chiappori and Salanié (2016), it is not possible to identify the marital surplus without further imposing a structure on the idiosyncratic terms. This is because the analyst cannot observe how people match based on unobserved traits. Following Choo and Siow (2006), I impose the separability assumption, which restricts matching on unobserved traits:

Assumption 1 (Separability). *The joint surplus from a marriage between a type I man and a type J woman is of the form*

$$z_{ij} = Z^{IJ} + \alpha_i^J + \beta_j^I \ . \tag{1.4}$$

This assumption allows for matching on unobservable traits, but conditional on the observed types of both spouses. For example, α_i^J reflects that a marriage between Mr. $i \in I$ and Ms. $j \in J$ may occur because Mr. i has unobservable traits (e.g. a certain hobby) that type J women value when choosing a partner. Moreover, α_i^J can also reflect that Mr. i has idiosyncratic preferences for type J women. Similar implications hold for β_j^I. However, the separability assumption does not allow the matching on unobserved traits of both spouses. For example, this rules out matching that occurs because Mr. i has idiosyncratic preference for some unobserved traits of Ms. j.

The separability assumption leads to the following property, which is crucial for identification:

Proposition 1 (Choo and Siow, 2006; Chiappori, Salanié, and Weiss, 2017). *For any stable matching, there exists values U^{IJ} and V^{IJ} satisfying the following property:*

- *Each man i will match with a woman of type J that maximizes $U^{IJ} + \alpha_i^J$ over $\tilde{\mathcal{F}}$*
- *Each woman j will match with a man of type I that maximizes $V^{IJ} + \beta_j^I$ over $\tilde{\mathcal{M}}$.*
- *$U^{I\emptyset}$ and $V^{\emptyset J}$ are normalized to be zero.*
- *$U^{IJ} + V^{IJ} = Z^{IJ}$ if (I, J) matches exist.*

Proof. See Chiappori, Salanié, and Weiss (2017).

U^{IJ} (resp. V^{IJ}) can be interpreted as the husband's (resp. wife's) portion of the deterministic part of the joint marital surplus that is shared between the spouses. An important consequence of Proposition 1 is that the separability assumption simplifies the two-sided matching problem by turning it into a series of discrete choice problem. Husband's share of the surplus, which is U^{IJ}, can be obtained from a man i's problem of choosing a partner type (or choosing not to marry) that maximizes his utility – i.e. a maximization of $U^{IJ} + \alpha_i^J$ over $\tilde{\mathcal{F}}$. Given U^{IJ}, wife's share of the surplus is written as $V^{IJ} = Z^{IJ} - U^{IJ}$. This can be similarly obtained through a woman j's problem of choosing a partner type (or choosing not to marry) that maximizes her utility, *taking into account* the surplus the husband takes from each type of marriage – i.e. a maximization of $Z^{IJ} - U^{IJ} + \beta_j^I$ over $\tilde{\mathcal{M}}$ given all U^{IJ}. Then, we can identify the marital surplus Z^{IJ}, which is simply a summation of U^{IJ} and V^{IJ}.

Marital Surplus: Following a common practice in the literature, I assume that the unobserved heterogeneities α_i^J and β_j^I are distributed as standard type-I extreme values.[20] Then, solving the model in a standard way (Choo and Siow, 2006), I get the following formula for Z^{IJ} for husband's type I and wife's type J:

$$Z^{IJ} = ln\Big(\frac{(\mu^{IJ})^2}{\mu^{I\emptyset}\mu^{\emptyset J}}\Big) \tag{1.5}$$

Because Z^{IJ} is a function of number of marrieds and singles, marital surplus can be recovered from the observed matching patterns, which is the equilibrium outcomes. Note that, unlike raw marriage rate, the above measure of marital surplus controls for the effects of demographic composition, by scaling the proportion of I, J marriages by the geometric average of the proportion of unmarrieds of those racial groups.

The notion of marital surplus can encompass any economic, social or other benefits associated

[20] Galichon and Salanié (2022) show that any distributions for the random terms can be used to identify the marital surplus, as long as these distributions are known ex ante.

with (I,J) marriage. Hence, Z^{IJ} for certain types of interracial marriage can have low values if there are high costs (e.g. high social stigma, discrimination, etc.) attached to those types of marriage. What marital surplus *cannot* tell us is which party drives the value of the joint surplus. For example, if the marriage between a Black man and a White woman has a high value of joint surplus, we cannot distinguish whether it is because Black men value marriage with White women more or it is because White women value marriage with Black men more.

Expected utilities: Another object of interest, which will be used throughout this paper, is the type-specific expected utilities from the marriage market. This can also be easily identified and estimated in this framework. As shown in Choo and Siow (2006), the expected utility from the marriage market for male type I is the following:

$$\bar{u}^I = E\Big[\max_J(U^{IJ} + \alpha_i^J)\Big] = ln\Big(\sum_j exp(U^{IJ}) + 1\Big) = -ln(Pr(single \mid I)) \tag{1.6}$$

The above equation shows that the expected utility of type I men can be fully expressed by their probability of being single, which is a well-established property of assuming Gumbel distributed idiosyncratic terms in a discrete choice framework. A similar result applies to the female type J, and I denote $\bar{v}^J$ the expected utility of women of type J.

One remark is that the expected utility that each group gets from the marriage market can be interpreted as *price* in the marriage market. $\bar{u}^I$ is the price that a woman has to pay to marry type I men; after paying the price, she keeps what is left of the joint surplus from marrying type I men. Similarly, $\bar{v}^J$ is the price that a man has to pay to marry type J women. Like the usual prices in any type of market, these expected utilities play an important role that equate demand and supply for each type of partners in the marriage market.

1.4.3 The System of Equilibrium Matching Functions

The matching model yields a system of equilibrium matching functions that link population distribution and marital surplus to equilibrium matching patterns. These functions allow counterfactual simulations and comparative statics, which will be used in Section 1.5 and Section 1.6.

To obtain this system of matching functions, I begin by re-arranging the marital surplus formula (Equation (1.5)) as the following:

$$\mu_t^{IJ} = exp\Big(\frac{Z^{IJ}}{2}\Big)\sqrt{\mu^{I\emptyset}\mu^{\emptyset J}} \tag{1.7}$$

Next, I plug the above expression into the feasibility constraints (Equations (1.1) and (1.2)) to obtain:

$$n^I = \mu^{I\emptyset} + \sum_J exp\Big(\frac{Z^{IJ}}{2}\Big)\sqrt{\mu^{I\emptyset}\mu^{\emptyset J}} \quad \forall\ I \tag{1.8}$$

$$m^J = \mu^{\emptyset J} + \sum_I exp\Big(\frac{Z^{IJ}}{2}\Big)\sqrt{\mu^{I\emptyset}\mu^{\emptyset J}} \quad \forall\ J \tag{1.9}$$

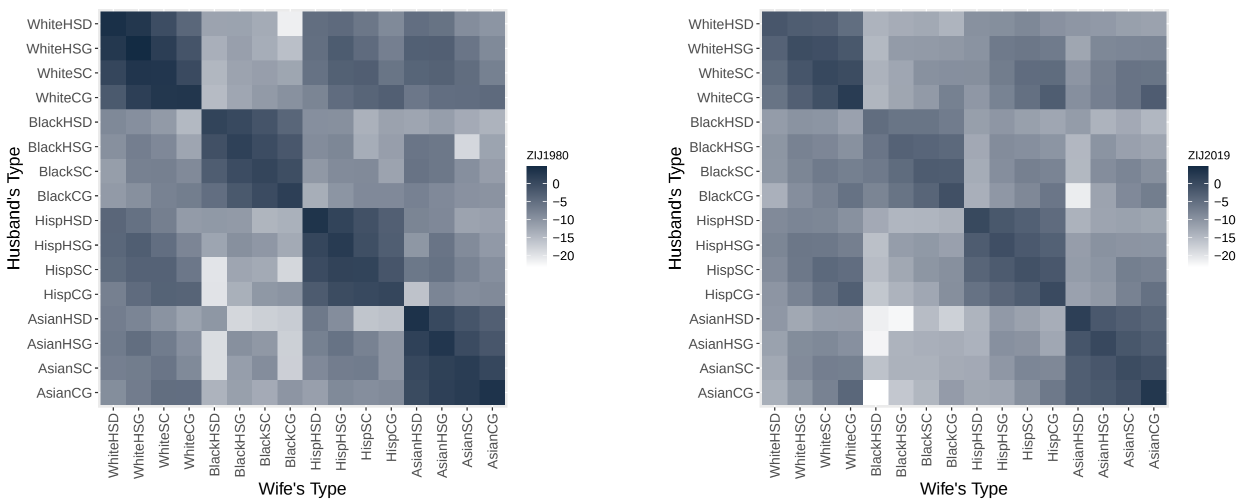
Let K be the total number of types for I and J, respectively. Then, Equations (1.8) and (1.9) define a system of $2K$ matching equations with $2K$ unknowns, which are the number of single men of each type ($\mu^{I\emptyset}$) and the number of single women of each type ($\mu^{\emptyset J}$) for all I, J.

The model primitives for this system are the vector of number of each type men (denoted as $\mathbf{n}$), the vector of number of each type women (denoted as $\mathbf{m}$), and the marital surplus matrix (denoted as $\mathbf{Z}$).The counterfactual simulations can be performed by deriving new equilibrium sorting patterns using the system of Equations (1.7), (1.8), and (1.9) with any counterfactual population distribution $(\mathbf{n}, \mathbf{m})$ and/or marital surplus $\mathbf{Z}$. Moreover, another interesting but unexplored feature of this system of matching functions is that it can be used to decompose the changes in equilibrium sorting patterns into contributions made by population changes and marital surplus changes. I demonstrate how this can be done in Section 1.6.

1.4.4 Descriptive Statistics: Estimated Marital Surplus

I estimate the marital surplus matrix $\mathbf{Z}_t$ for each year t using the empirical marriage patterns in the data. In this section, I provide descriptive statistics of the estimated marital surplus, which I denote $\hat{\mathbf{Z}}_t$. I document the evolutions of the value of interracial marriage across race and education groups.

Figure 1.3: Estimated Marital Surplus $\hat{\mathbf{Z}}_t$, 1980 vs 2019



(a) 1980 (b) 2019

<u>Note:</u> This figure shows a heatmap for estimated marital surplus $\hat{Z}_t^{IJ}$ for the survey year 1980 (Panel (a)) and the survey year 2019 (Panel (b)), respectively. I refers to husband's type (Row) and J refers to wife's type (Column). HSD: high school dropout, HSG: high school graduate with no college education, SC: less than 4 years of college education, and CG: 4 years of college education or more.

In Figure 1.3, I plot the heatmaps of the marital surplus for the survey years 1980 and 2019. Panel (a) confirms that the US marriage market was largely segregated by race in 1980: for all races, the same-race marriages exhibit highest values of marital surplus in 1980. Panel (b) shows several notable patterns. First, compared to 1980, the values of marital surplus have generally gone down for most marriages in 2019, especially for the marriages involving lower-educated people. This reflects a well-known retreat from marriage in the US (Lundberg, Pollak, and Stearns, 2016). Second, the marriage market is still largely segregated by race in 2019; the same-race marriages still exhibit highest values of marital surplus across all races. Third, within each block of interracial marriages, the values of marital surplus are highest for college graduates in 2019.

To better understand how the joint surplus from interracial marriage have changed compared to same-race marriage for different race and education groups, I report selected marital surplus for marriages and the corresponding changes in the marital surplus over the 1980-2019 period. Table 1.1 reports selected $\hat{Z}_t^{IJ}$ for marriages involving a White spouse, and Table 1.2 reports selected $\hat{Z}_t^{IJ}$ for marriages involving a Black spouse. When describing the changes in marital surplus below, I focus on the sign of the changes rather than on the magnitude of the changes. This is because marital surplus is a non-linear function of number of marriages and singles as shown in Equation (1.5), which makes it difficult to directly compare the levels of the changes in $\hat{Z}_t^{IJ}$ across $\hat{Z}_t^{IJ}$s with differing starting values.

Table 1.1: Selected Marital Surplus Involving White Spouse

	Panel A: Marital surplus for CG couple				**Panel B: Marital surplus for HSG couple**			
		1980	2019	$\Delta^{2019-1980}$		1980	2019	$\Delta^{2019-1980}$
White-White	$Z^{WhiteCG,WhiteCG}$	3.01	2.13	**-0.88**	$Z^{WhiteHSG,WhiteHSG}$	4.74	-0.38	**-5.12**
White-Black	$Z^{WhiteCG,BlackCG}$	-9.58	-7.48	**+2.10**	$Z^{WhiteHSG,BlackHSG}$	-11.47	-10.84	**+0.63**
	$Z^{BlackCG,WhiteCG}$	-7.08	-5.55	**+1.53**	$Z^{BlackHSG,WhiteHSG}$	-7.21	-7.67	**-0.45**
White-Hispanic	$Z^{WhiteCG,HispCG}$	-3.01	-2.61	**+0.40**	$Z^{WhiteHSG,HispHSG}$	-2.46	-6.64	**-4.17**
	$Z^{HispCG,WhiteCG}$	-3.59	-2.92	**+0.67**	$Z^{HispHSG,WhiteHSG}$	-2.79	-6.24	**-3.44**
White-Asian	$Z^{WhiteCG,AsianCG}$	-4.50	-2.59	**+1.91**	$Z^{WhiteHSG,AsianHSG}$	-2.99	-8.43	**-5.44**
	$Z^{AsianCG,WhiteCG}$	-5.07	-4.07	**+1.00**	$Z^{AsianHSG,WhiteHSG}$	-5.00	-9.06	**-4.06**

Notes: This table reports selected marital surplus for marriages involving at least one White spouse. Panel A reports marital surplus for marriages where both spouses are college graduates. Panel B reports marital surplus for marriages where both spouses are high school graduates. For Z^{IJ}, I refers to husband's type and J refers to wife's type. $\Delta^{2019-1980}$ denotes the change in corresponding marital surplus from 1980 to 2019. CG refers to 4-year college graduates, and HSG refers to high school graduates or equivalent GED.

Table 1.1 reveals several implications about the evolution of the values of interracial marriage. First, it has become less costly to marry across racial lines for college graduates, but no evidence is shown for high school graduates. Panel A shows that the marital surpluses of all interracial marriages involving a White college-educated spouse have increased over the past four decades, while the value for the same-race marriage between White college-educated men and women has decreased. In contrast, Panel B shows that the marital surpluses of most interracial marriages, as well as the same-race marriage, have gone down for marriages involving a White high school graduate spouse. Notably, the values of interracial marriages between White high school graduates and Hispanic or Asian high school graduates have experienced a sharp decline over the past four decades. These different trends by education in the value of interracial marriage is consistent with the arguments in social sciences that education is becoming increasingly more important than race in marriage (Kalmijn, 1991; Schwartz, 2013), and that college graduates are more open to interracial marriage (Livingston and Brown, 2017).

Second, the barriers to marrying across racial lines widely differ across gender and race. Black-White marriages exhibit the lowest value among the interracial marriages involving a White spouse. Among Black-White marriages, marriages between Black men and White women have higher values than marriages between White men and Black women, both in 1980 and in 2019. This confirms that there are higher social costs for Black-White marriages compared to other types of interracial marriages, especially for the marriages involving Black women, as widely conjectured (Fryer Jr., 2007; O'Flaherty, 2015). There is also a gender difference in White-Asian marriage: marriage between White men and Asian women have higher value than marriage between Asian men and White women. It is worth noting that these patterns of the marital surplus resemble the prior evidence on the racial preferences in the dating market. Both Hitsch, Hortacsu, and Ariely (2010) and Lin and Lundquist (2013) show using the data from dating applications that Black women and the Asian men are the groups that are least likely to send to or receive messages from dating candidates outside their race.

Table 1.2: Selected Marital Surplus Involving Black Spouse

	Panel A: Marital surplus for CG couple				**Panel B: Marital surplus for HSG couple**			
		1980	2019	$\Delta^{2019-1980}$		1980	2019	$\Delta^{2019-1980}$
Black-Black	$Z^{BlackCG,BlackCG}$	1.63	-0.86	**-2.49**	$Z^{BlackHSG,BlackHSG}$	1.33	-3.40	**-4.74**
Black-White	$Z^{BlackCG,WhiteCG}$	-7.08	-5.55	**+1.53**	$Z^{BlackHSG,WhiteHSG}$	-7.21	-7.67	**-0.45**
	$Z^{WhiteCG,BlackCG}$	-9.58	-7.48	**+2.10**	$Z^{WhiteHSG,BlackHSG}$	-11.47	-10.84	**+0.63**
Black-Hispanic	$Z^{BlackCG,HispCG}$	-8.65	-6.10	**+2.55**	$Z^{BlackHSG,HispHSG}$	-8.30	-8.97	**-0.67**
	$Z^{HispCG,BlackCG}$	-9.99	-9.32	**+0.67**	$Z^{HispHSG,BlackHSG}$	-9.45	-11.12	**-1.67**
Black-Asian	$Z^{BlackCG,AsianCG}$	-9.90	-7.14	**+2.76**	$Z^{BlackHSG,AsianHSG}$	-6.35	-9.95	**-3.60**
	$Z^{AsianCG,BlackCG}$	-10.17	-10.96	**-0.79**	$Z^{AsianHSG,BlackHSG}$	-9.50	-13.87	**-4.38**

Notes: This table reports selected marital surplus for marriages involving at least one Black spouse. Panel A reports marital surplus for marriages where both spouses are college graduates. Panel B reports marital surplus for marriages where both spouses are high school graduates. For $Z^{I,J}$, I refers to husband's type and J refers to wife's type. $\Delta^{2019-1980}$ denotes the change in corresponding marital surplus from 1980 to 2019. CG refers to 4-year college graduates, and HSG refers to high school graduates or equivalent GED.

Similar to Table 1.1, Table 1.2 also shows that the gains from interracial marriage involving a Black spouse have only increased for the college-educated. The values of Black-Hispanic marriages and Black-Asian marriages are lower than the value of Black-White marriages in both years. This shows that there are higher social or cultural barriers to marry across races among minorities, even after accounting for their relatively small proportions in the population. The estimates also show that interracial marriages involving Black women have lower values than the interracial marriage involving Black men for all cases, which again confirms that there are higher social barriers for Black women to marry out of their race than for Black men.

While it is useful to understand how the structural gains from interracial marriage have changed, what matters more is how these changes have affected individual welfare. For example, how did the increase in the gains from interracial marriage among college graduates shown in Table 1.1 affect individual welfare in the marriage market? Especially since there have been disproportionate changes in the gains from interracial marriage, not every group may have benefitted from the changes in the structure of marital surplus. In order to evaluate the welfare implications of these changes, I need to (i) construct a measure of welfare from marital desegregation for each group and (ii) estimate how these various changes in marital surplus over time have affected the welfare of each group. These will be done in the following sections.

1.5 Measuring Gains from Marital Desegregation

In this section, I measure the welfare gain from marital desegregation for each group. The goal is to understand the welfare implications of the heterogeneous trends of marrying out across groups shown in Figure 1.1. Specifically, I aim to understand whether racial desegregation has improved welfare even for the groups who marry out less than their counterparts, such as Black women and White women.

The welfare gain captures how much each group has benefitted from the option of interracial marriage for each survey year. In order to capture this effect, there needs to be a benchmark state where interracial marriage is not allowed for each year. To this end, I construct a “racially segregated marriage market" using the matching model presented in Section 1.4. The idea is to construct a counterfactual world where everything is to be the same as the actual world, *except* for the costs to interracial marriage, which are set to be infinitely high for everyone. All individuals re-optimize their marriage choices in this counterfactual marriage market, thereby resulting in new equilibrium matching patterns. Because the only difference from the actual market is that there is no option of interracial marriage in the segregation scenario, any deviation from the actual marriage patterns can be fully attributed to removal of interracial marriage. Hence, I isolate the effects of the option of interracial marriage by comparing the observed marriage patterns and the new equilibrium marriage patterns in a racially segregated marriage market.

Section 1.5.1 describes the estimation strategy in detail. Section 1.5.2 presents the results on the welfare gains from marital desegregation.

1.5.1 Estimation Strategy

Counterfactual simulation for complete segregation: I describe the steps to compute the counterfactual equilibrium marriage patterns for the scenario of complete racial segregation.

- **Step 1:** For each survey year t, I take the marital surplus matrix $\hat{\mathbf{Z}}_t$ that is estimated in Section 1.4.4.

- **Step 2:** For each $\hat{\mathbf{Z}}_t$, I replace $\hat{Z}_t^{IJ}$ by minus infinity for all (I, J) that correspond to interracial marriage ($R_i \neq R_j$). This guarantees that interracial marriages do not happen. I keep the marital surpluses for all same-race marriage at their corresponding values in $\hat{\mathbf{Z}}_t$. I denote $\hat{\mathbf{Z}}_t^{Segregated}$ the resulting counterfactual marital surplus matrix for complete racial segregation.

- **Step 3:** I compute the counterfactual marriage patterns for each survey year t, using $\hat{\mathbf{Z}}_t^{Segregated}$ and the actual population vectors $\mathbf{n}_t$ and $\mathbf{m}_t$,. This is done by applying the Iterative Projection Fitting Procedure (IPFP) on the system of matching functions represented by Equations (1.8) and (1.9) in Section 1.4.3.[21]

[21] Galichon and Salanié (2022) explain that IPFP is an efficient and fast way to solve for the stable matching. This

Through the above procedures, I obtain the counterfactual equilibrium numbers of single men and women of each type for each survey year. One remark is that complete racial segregation can be represented by *any* marital surplus matrix where the entries for interracial marriages have infinitely negative values. However, because the objective is to only capture the changes in sorting patterns due to changes in the value of interracial marriage, I choose the values of same-race marriages in $\hat{\mathbf{Z}}_t^{Segregated}$ to be same as their values in $\hat{\mathbf{Z}}_t$.

Welfare gains from marital desegregation: Using the counterfactual sorting patterns, I define and estimate "welfare gains from marital desegregation." This measure captures the excess utility each group receives in the actual marriage market over what they would get in a completely racially segregated marriage market.

Formally, the welfare gains from marital desegregation for each man type I are defined as the following:

$$Gain_{m,t}^{I} = \underbrace{\bar{u}_t^{I,Desegregated}}_{Actual} - \underbrace{\bar{u}_t^{I,Segregated}}_{Counterfactual} \tag{1.10}$$

where $\bar{u}_t^{I,Desegregated}$ is the type-specific expected utility in the actual marriage market and $\bar{u}_t^{I,Segregated}$ is the corresponding expected utility in the racially segregated marriage market in year t. $Gain_{t,m}^{I}$ captures the *additional* expected utilities that type I men receive from the lowered cost of interracial marriage in year t.

Analogously, for each woman type J, the welfare gains from marital desegregation are:

$$Gain_{f,t}^{J} = \underbrace{\bar{v}_t^{J,Desegregated}}_{Actual} - \underbrace{\bar{v}_t^{J,Segregated}}_{Counterfactual} \tag{1.11}$$

As shown in Equation (1.6), the type-specific expected utilities are fully summarized by the

algorithm solves the system of equations defined by Equations (1.8) and (1.9) iteratively, starting from the vector of arbitrary guesses $\mu_{(0)}^{I}$ and $\mu_{(0)}^{J}$. The intuition behind this algorithm is that the average utilities ($\bar{u}^I$ and $\bar{v}^J$) of each type of men and women act as *prices* in the marriage market that equate demand and supply of partners. Hence, the algorithm adjusts the prices alternatively on each side of the market until it reaches the stable matching.

probabilities of singlehood for each type under the assumption of Gumbel distributed stochastic terms. Therefore, the welfare gain essentially can be understood as the difference in the prevalence of singlehood between the actual world and the counterfactual world with complete racial segregation. For example, if fewer type I men remain single in the actual world than in the completely racially segregated world, it means that marital racial integration has increased the average welfare of type I men through an increase in the probabilities of marriage.

For ease of interpretation, I rescale the welfare gains to represent the percentage change in the single rate that would occur when the marriage market is completely segregated. To explain, note that $Gain^{I}_{m,t}$ can be re-written as:

$$
\begin{aligned}
Gain^{I}_{m,t} &= ln\Big(Pr(Single \mid I, t, Segregated)\Big) - ln\Big(Pr(Single \mid I, t, Desegregated)\Big) \\
&\approx \frac{Pr(Single \mid I, t, Segregated) - Pr(Single \mid I, t, Desegregated)}{Pr(Single \mid I, t, Desegregated)}
\end{aligned}
$$

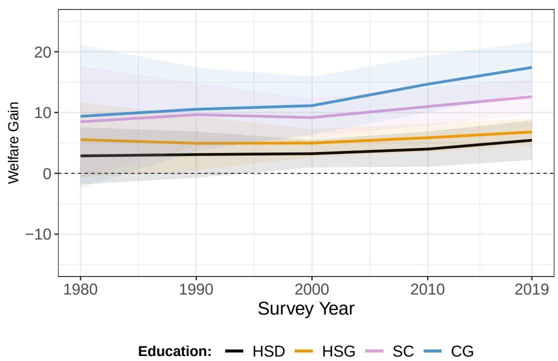
Therefore, the welfare gain multiplied by 100 can be interpreted as the percentage change in the single rate of type I men that would occur if we move from the current state to complete segregation in each year t.

Remark: This welfare gain measure is silent about the mechanisms through which marital desegregation operates. A positive utility gain *only captures* the fact that the single rate of a given type is lower in the actual world than in the perfectly segregated world. It *does not* tell us with whom those individuals marry more or what drives the welfare gain. In Section 1.6, I investigate the specific mechanisms that drive the evolution of each welfare gain over time.

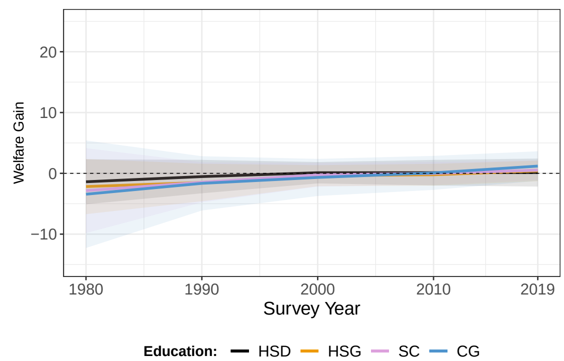
1.5.2 Results

Figure 1.4 presents the estimated welfare gains from marital desegregation over the past four decades for Blacks and Whites. To facilitate the comparison of the magnitude of the welfare gains, I use the same scale on the y-axis for all groups. I discuss the results for each group below.

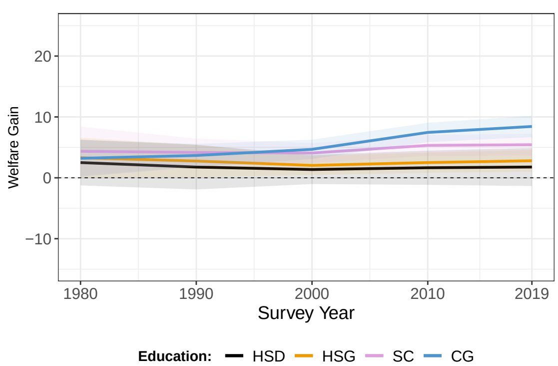
Figure 1.4: Type-Specific Welfare Gains from Marital Desegregation



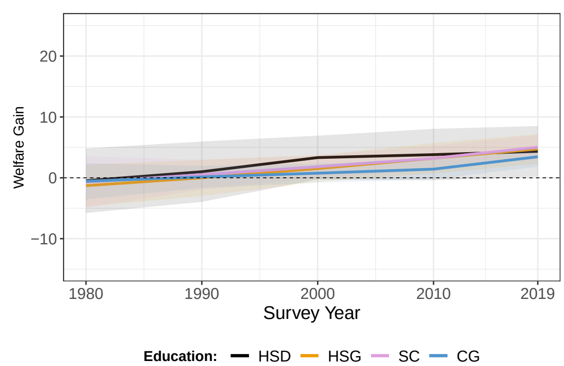
(a) Black Men



(b) Black Women



(c) White Men



(d) White Women

Note: These figures plot the welfare gain from marital desegregation as defined by Equation (1.10) and Equation (1.11) for each specified type of men and women. Data used to calculate the gains are: 1980-2000 Decennial Census, 2010 and 2019 5-Year ACS. I focus on age 37-46 men and age 35-44 women for each survey year. Further details on the sample restriction are described in Section 3.3. Shade for each line refers to the 95% confidence interval. Standard errors are calculated from the sampling variation in the data. *HSD*: high school dropout, *HSG*: high school graduate with no college education, *SC*: less than 4 years of college education, and *CG*: 4 years of college education or more.

Results for Black men: In 1980, Black men had on average positive welfare gains from marital desegregation as shown in Figure 1.4a, even though these positive gains were not significantly different from zero. Over the years, the most educated Black men experienced the highest increase in welfare gains. In 2019, the magnitude of the welfare gains for college-educated Black men is substantial: in the absence of marital desegregation, the probability of being single would be on average 17.5% higher for the college-educated Black men. For all years, there is a clear positive relationship between Black men's education level and the welfare gains they receive from the desegregated marriage market.

Results for Black women: In contrast, Figure 1.4b shows that Black women did not gain from marital desegregation across all years. While the welfare gain for college-educated Black women increased over time from the negative mean value in 1980, this increase is not as large as what college-educated Black men experienced.

This reveals a less-discussed aspect of the currently low marriage rates of Black women. Previous literature has focused on the explanations related to the within-race marriage market; the low marriage rate of Black women is typically attributed to the lack of marriageable Black men (Charles and Luoh, 2010; Liu, 2020; Caucutt, Guner, and Rauh, 2021). Figure 1.4b provides an explanation pertaining to the across-race marriage market. Black women do not benefit from marital desegregation at all, which further contributes to their currently low marriage rates.

Results for White men: In 1980, all White men received on average positive welfare gains from marital racial desegregation as shown in Figure 1.4c. These gains are statistically significant except for the high school dropouts. Over time, college-educated White men experienced a larger increase in welfare gains than other groups: in 2019, marital desegregation led to a reduction of in their probability of being single by 8% compared to the complete segregation scenario. In contrast, non-college-educated White men experienced a slight decrease in the welfare gains over time. In 2019, the welfare gains for high school graduate White men are translated into the reduction in the probability of being single by 2% compared to the complete segregation scenario. From 2000 onward, there is a clear positive relationship between White men's education level and the welfare gains they receive from the desegregated marriage market.

Results for White women: Welfare gains for White women show different patterns. While all White women did not gain at all from marital racial desegregation in 1980, they increasingly gained more over time. Notably, there is no clear education difference in the trends, unlike the case of White men. In 2019, marital racial desegregation reduced the probability of being single for White women, across all education levels, by 3 ~ 5% relative to the complete segregation scenario.

These results show that the welfare gains have not evolved in the same way even within each race. College-educated men benefited the most from racial desegregation in the recent years among Blacks and Whites. In the next section, I investigate why welfare gains from marital desegregation have evolved differently across groups.

1.6 Decomposition

The welfare gains from marital desegregation can be affected by both the population changes and the marital surplus changes. For example, the larger increase in the gains for college-educated Black men can be a byproduct of population changes that there are now more college-educated women than college-educated men in the marriage market, as shown in Figure 1.2. On the other hand, the increasingly larger gains for college-educated Black men can also be due to the rise in the joint surplus from interracial marriage among college-educated that is shown in Section 1.4.4.

In this section, I examine how changing population and changing marital surplus have shaped the unequal gains from marital desegregation. I implement a decomposition method, for the first time in the marriage literature, to measure the contributions of various market-level changes in population and in marital surplus on welfare gains for each type of men and women. Before describing the method, I first discuss the estimation challenges. Any single change in the population or in the structural value of marriage can affect the overall sorting patterns and the welfare of *all* men and women through the equilibrium channel. In the US marriage market, there have been a large number of changes in the population (as discussed in Section 1.2) and changes in the gains from various types of marriage (as shown in Section 1.4.4) over the past four decades. Moreover, all these market-level changes took place *gradually* over time. It is challenging to summarize the equilibrium effects from such large number of different changes that happened in the marriage market over a long time horizon.

To address this challenge, I combine the implicit function theorem and a fine-tuning method to link four decades of changes in welfare gains to the four decades of changes in population and in marital surplus. This method accounts for both the general equilibrium effects and the gradual nature of the market-level changes. The benefit of this method is that it can identify which changes played the biggest role in driving the change in welfare gains for each group. To the best of my knowledge, this decomposition has never been implemented in the marriage market literature.

Section 1.6.1 describes the method. Section 1.6.2 presents the decomposition results.

1.6.1 Overview of the Method

In this subsection, I provide a step-by-step description of the decomposition method.

Step 1: Implicit differentiation. The first step of this method is to use the implicit function theorem (IFT) on the system of equilibrium matching functions defined by Equations (1.8) and (1.9). The goal of this step is to measure how small changes in the model primitives affect the equilibrium number of single men and women of each type. To facilitate the application of IFT, I apply the following changes of variables: $\tilde{Z}_t^{IJ} = exp\left(\frac{Z_t^{IJ}}{2}\right)$ and $s_t^{I\emptyset} = \sqrt{\mu_t^{I\emptyset}}$ and $s_t^{\emptyset J} = \sqrt{\mu_t^{\emptyset J}}$. I use $\tilde{\boldsymbol{\theta}}_t = (\mathbf{n}_t, \mathbf{m}_t, \tilde{\mathbf{Z}}_t)$ to denote the complete set of model primitives.[22] Then, Equations (1.8) and (1.9)

[22]Full expansion of $\tilde{\boldsymbol{\theta}}_t$ is $\tilde{\boldsymbol{\theta}}_t = \left(n_t^1, \ldots, n_t^K, m_t^1, \ldots, m_t^K, \tilde{Z}_t^{11}, \tilde{Z}_t^{12}, \ldots, \tilde{Z}_t^{KK}\right)$. This vector has $2K + K^2$ components; because $K = 16$ in my setting, $\tilde{\boldsymbol{\theta}}_t$ has 288 components.

are re-written as:

$$F^I(\tilde{\boldsymbol{\theta}}_t) = (s_t^{I\emptyset})^2 + \sum_J \tilde{Z}_t^{IJ} s_t^{I\emptyset} s_t^{\emptyset J} - n_t^I = 0 \qquad \forall\ I \tag{1.12}$$

$$G^J(\tilde{\boldsymbol{\theta}}_t) = (s_t^{\emptyset J})^2 + \sum_I \tilde{Z}_t^{IJ} s_t^{I\emptyset} s_t^{\emptyset J} - m_t^J = 0 \qquad \forall\ J \tag{1.13}$$

As the $2K$ matching equations defined by Equations (1.12) and (1.13) are not independent, I need to apply the IFT on the *whole* system in order to get partial derivatives of $s_t^{I\emptyset}$ for all I and $s_t^{\emptyset J}$ for all J with respect to each of the marginal changes in the model primitives $\tilde{\boldsymbol{\theta}}_t$.

For the brevity of notation, I use $\mathbf{s} = (s^{1\emptyset}, \ldots, s^{K\emptyset}, s^{\emptyset 1}, \ldots, s^{\emptyset K})$ to denote a vector of the square root of the number of singles of each type of individuals. I also denote $\mathbf{F}$ as a vector for F^I and $\mathbf{G}$ as a vector for G^J. Applying the IFT on the system of equations (1.12) and (1.13) leads to the following Jacobian matrix of partial derivatives of $\mathbf{s}_t$:

$$\left[\frac{\partial \mathbf{s}_t}{\partial \tilde{\boldsymbol{\theta}}_t}\right]_{(2K)\times(2K+K^2)} = -\begin{bmatrix} \dfrac{\partial \mathbf{F}}{\partial \mathbf{s}_t} \\ \\ \dfrac{\partial \mathbf{G}}{\partial \mathbf{s}_t} \end{bmatrix}^{-1}_{(2K)\times(2K)} \begin{bmatrix} \dfrac{\partial \mathbf{F}}{\partial \tilde{\boldsymbol{\theta}}_t} \\ \\ \dfrac{\partial \mathbf{G}}{\partial \tilde{\boldsymbol{\theta}}_t} \end{bmatrix}_{(2K)\times(2K+K^2)} \tag{1.14}$$

The full solution for the partial derivatives is presented in Appendix A.2.1. This Jacobian matrix summarizes how a small change in each model primitive $\tilde{\theta}_t^k$ affects the equilibrium number of single men and women of each type.

Step 2: Linking the Jacobian to welfare gains from marital desegregation. Because the welfare gain is a function of equilibrium single rates as shown in Equations (1.10) and (1.11), it is straightforward to use the Jacobian matrix (Equation (1.14)) to understand how a small change in each $\tilde{\theta}^k$ affects the welfare gains for each type of man and woman.

To demonstrate, consider the expected utility for type I men. Recall that $\bar{u}_t^I = -ln(Pr(single|I,t)) =$

$-ln\left(\frac{\mu_t^{I\emptyset}}{n_t^I}\right)$ and $\mu_t^{I\emptyset} = (s_t^{I\emptyset})^2$. Then, the total differential of $\bar{u}_t^I$ is:

$$d\bar{u}_t^I = \frac{1}{n_t^I}dn^I - \frac{2}{s_t^{I\emptyset}}\left(\frac{\partial s_t^{I\emptyset}}{\partial \tilde{\boldsymbol{\theta}}_t}d\tilde{\boldsymbol{\theta}}_t\right) \tag{1.15}$$

where the partial derivative $\frac{\partial s_t^{I\emptyset}}{\partial \tilde{\boldsymbol{\theta}}_t}$ is from the Jacobian matrix shown in Equation (1.14). Note that the right hand side of Equation (1.15) can be linearly decomposed into parts that are attributed by each change in the model primitive $d\tilde{\theta}_t^k$. This is the key feature that allows the decomposition of the welfare gain into contributions made by each change in the population distribution and the marital surplus, which will be further discussed in the next steps.

Because the welfare gain is the difference between the expected utility in the actual world and the expected utility in the completely segregated world, this can be expressed analogously using Equation (1.15).

Step 3: Fine-tuning method to link four decades of changes in $\tilde{\boldsymbol{\theta}}$. The implicit function theorem approach only applies to small changes in the model primitives. However, the objective is to understand the effects of four decades of changes in population and in marital surplus on welfare gains. Using the implicit function approach for such large changes may led to an incorrect decomposition.

To better approximate the effect of changes in model primitives on changes in welfare gains over the past four decades, I implement a fine-tuning method following Judd (1998). This method decomposes the large changes in the model primitives into a series of infinitesimal changes. Using this method, I evaluate the differentials for each infinitesimal change and update the approximation along the path of infinitesimal changes. I apply this method for each decade within the 1980-2019 period, based on available survey years.

To give a concrete example, I consider the changes from 1980 to 1990. I denote 1980 as $\tau = 0$ and 1990 as $\tau = 1$. Then $\tilde{\boldsymbol{\theta}}_0$ (resp. $\tilde{\boldsymbol{\theta}}_1$) is the vector of the values of model primitives in 1980 (resp.

in 1990). Consider the homotopy:

$$\tilde{\boldsymbol{\theta}}_\tau = \tau\tilde{\boldsymbol{\theta}}_1 + (1-\tau)\tilde{\boldsymbol{\theta}}_0, \quad \tau \in [0,1]$$

which defines a series of intermediate values of the model primitives with interval $d\tau$ between observed values at $\tau = 0$ and $\tau = 1$. Because $\tilde{\boldsymbol{\theta}}_\tau$ is now a function of τ, Equation (1.15) is re-written as:

$$d\bar{u}^I_\tau = \frac{1}{n^I_\tau}(n^I_1 - n^I_0)d\tau - \frac{2}{s^{I\emptyset}_\tau}\left(\frac{\partial s^{I\emptyset}_\tau}{\partial\tilde{\boldsymbol{\theta}}_\tau}(\tilde{\boldsymbol{\theta}}_1 - \tilde{\boldsymbol{\theta}}_0)d\tau\right) \tag{1.16}$$

Using the above specification, I can use infinitesimal change $d\tau$ to evaluate and decompose the infinitesimal changes in $\bar{u}^I_t$ between years 1980 and 1990. Note that this method accounts for the *gradual* nature of the changes in population and in marital preferences. In practice, I specify $d\tau = 0.001$ when estimating Equation (1.16) for each decade. Summing the decompositions of infinitesimal changes of the expected utility over the 1980-1990 period gives a better approximation of $\Delta\bar{u}^I_t$ than directly using the observed 10-year changes in model primitives to evaluate Equation (1.15).

Application to the four decades of changes in welfare gains from racial desegregation is done analogously. Further details on how I perform this method are documented in Appendix A.2.2.

Step 4: Decomposition. The above steps lead to a linear decomposition of four decades of changes in welfare gains into contributions from changes in population and in marital surplus. For instance, the welfare gain from marital desegregation of type I man between 1980 to 2019 are decomposed into the following:

$$\begin{aligned}\Delta^{2019-1980}Gain^I = {} & (Contribution\ by\ \Delta n^1) + \ldots + (Contribution\ by\ \Delta n^K) \\ & + (Contribution\ by\ \Delta m^1) + \ldots + (Contribution\ by\ \Delta m^K) \\ & + (Contribution\ by\ \Delta Z^{11}) + \ldots + (Contribution\ by\ \Delta Z^{KK}) \end{aligned} \tag{1.17}$$

As shown in Equation (1.17), this method can summarize a large number of the contributions from various market-level changes. Therefore, this allows me to identify which changes have driven the welfare gain from marital desegregation for each group of men and women over the past four decades.

I evaluate the validity of the decomposition method by comparing the estimated changes in welfare gains from the data (using Equations (1.10) and (1.11)) and the estimated welfare gains using the IFT approach. The latter is simply the total sum of contributions for each group, as represented by the right-hand side of Equation (1.17). Table 1.3 shows that the estimates based on the method closely match those based on the data for each group of man and woman. This confirms the validity of the method.

Table 1.3: Data vs. IFT: 1980-2019 Changes in Welfare Gains from Marital Desegregation

	Men		Women	
Type	Data	IFT	Data	IFT
WhiteHSD	-0.728	-0.730	4.826	4.827
WhiteHSG	-0.492	-0.494	6.018	6.021
WhiteSC	1.076	1.074	5.727	5.729
WhiteCG	5.231	5.230	4.020	4.021
BlackHSD	2.566	2.567	1.515	1.516
BlackHSG	1.254	1.255	2.575	2.576
BlackSC	4.114	4.115	3.366	3.366
BlackCG	8.028	8.027	4.635	4.637

Notes: This table reports the changes in (i) welfare gain of each group over the 1980-2019 period that is estimated from data and (ii) the corresponding changes estimated from the IFP method. “Data" column refers to the estimated change from the data, and “IFT" column refers to estimated changes using IFT according to Equation (1.17). $d\tau = 0.001$ is used when applying the fine-tuning method.

1.6.2 Decomposition Results

In this section, I start by documenting the contributions made by overall population changes and overall marital surplus changes. Recall that the welfare gain is interpreted as the percentage difference in the single rate that would occur in the absence of marital desegregation. Hence, $\Delta^{2019-1980}Gain$ in Table 1.4 represents the percentage point changes in these percentage differences over the 1980-2019 period.

Table 1.4 shows that the overall population changes and the overall marital surplus changes made different impacts across groups. This reveals that the underlying reasons behind the unequal gains from marital desegregation is complicated: some groups benefitted from the population changes, while other groups benefitted from marital preference changes.

For Blacks, the combined marital surplus changes had a positive and larger effect on the welfare gains than the combined population changes, across all groups. Notably, Black college-educated men have gained the most from the changes in marital surplus. The population changes only played a minor (and negative) role in the overall increase in welfare gains for Black college-educated men. This shows that the reversal of the gender gap in college education shown in Figure 1.2 did not drive the welfare gains for Black college-educated men.

Table 1.4: Decomposition of the 1980-2019 Changes in the Welfare Gain from Marital Desegregation

		Total Contribution by the Changes in:	
Type	$\Delta^{2019-1980}Gain$	Population	Marital Surplus
BlackCG Men	8.0	-2.5	10.6
BlackHSG Men	1.3	-3.1	4.3
BlackCG Women	4.6	0.8	3.8
BlackHSG Women	2.6	1.0	1.6
WhiteCG Men	5.2	6.8	-1.6
WhiteHSG Men	-0.5	5.4	-5.8
WhiteCG Women	4.0	-1.2	5.2
WhiteHSG Women	6.0	-0.7	6.7

Notes: This table presents the decomposition of the 1980-2019 changes in the welfare gains from marital desegregation for the specified type of individuals. $\Delta^{2019-1980}Gains$ is the change in the welfare gains for the specified group over the 1980-2019 period. “Population" Column shows the summation of all contributions by changes in population over the 1980-2019 period. “Marital Surplus" Column shows the summation of all contributions by changes in marital surplus over the 1980-2019 period..

A different picture emerges for Whites. For White men, the composite population changes made the positive contributions, whereas the composite marital surplus changes made the negative contributions to the welfare gains. This shows that the rise in the welfare gains from marital desegregation for the college-educated White men is not driven by the increase in the surplus from interracial marriage with non-White women. For White high school graduate men, the large negative force from marital surplus changes completely offset the positive contributions from population changes. In contrast, White women benefited from the overall marital surplus changes, and these positive contributions are larger than the negative contributions from population changes.

In the following subsections, I document the specific changes that made the largest contributions to the welfare gain of each group.

1.6.2.1 What drove the rise in welfare gains for Black college-educated men?

Table 1.5 presents top three positive and top three negative contributions from changes in marital surplus for college-educated Black men. The main finding is that $Z^{BlackCG,WhiteCG}$, the marital surplus for the marriage between Black college-educated men and White college-educated women, made the largest positive contribution. The magnitude of the contribution $Z^{BlackCG,WhiteCG}$ is substantial: it represents about 60% of the total change of their welfare gain. The contribution from $Z^{BlackCG,WhiteCG}$ is more than twice times larger than other top positive contributions. Positive contribution from $Z^{BlackCG,WhiteCG}$ is large enough to completely offset negative forces, such as the increase in the gains from marriage between White college-educated men and Black college-educated women (i.e. $Z^{WhiteCG,BlackCG}$ from the Top (-) Contributions).

Table 1.5: Decomposition: Top three contribution from changes in **Z**, Black CG Men

		(1)	(2)	(3)
Contribution	Top (+)	4.7 $Z^{BlackCG,WhiteCG}$	1.8 $Z^{BlackCG,BlackSC}$	1.5 $Z^{BlackCG,HispCG}$
	Top (-)	-0.6 $Z^{WhiteCG,BlackCG}$	-0.6 $Z^{BlackSC,BlackCG}$	-0.4 $Z^{BlackCG,AsianHSD}$

Notes: This table presents the top three positive and negative contributions from marital surplus to the 1980-2019 changes in the welfare gains from marital desegregation for Black college graduate men. For marital surplus Z^{IJ}, I refers to husband's type and J refers to wife's type.

Because $Z^{BlackCG,WhiteCG}$ has increased over time as shown in Table 1.2, the result reveals that the increase in the gains from intermarrying White college-educated women played a substantial role in driving up the welfare gains for Black college-educated men. It has to be noted that the matching model cannot distinguish precise reasons why the marital surplus for this pair has increased over time. However, this finding is consistent with the story of less social stigma over time in marrying out among the college-educated. Moreover, the finding is also consistent with the significant advances in earnings of college-educated Black men, as documented in Bayer and Charles (2018), that made them more attractive partners to White college-educated women.

Other notable findings in Table 1.5 include the positive contribution from $Z^{BlackCG,BlackSC}$, which is the joint surplus from marriage between Black college-educated men and Black some-college women. Appendix Figure A.3 shows that $Z^{BlackCG,BlackSC}$ has declined over time. Hence, this decomposition result suggests as the gains from marrying Black some-college women went down, that Black college-educated men benefitted from marital desegregation, relative to the segregation scenario. Furthermore, Table 1.5 additionally shows that Black college-educated men benefitted from the increase in the the gains from marrying Hispanic college-educated women.

1.6.2.2 Why did other groups within Blacks not gain as much?

Table 1.6 presents top three positive and top three negative contributions from changes in marital surplus for Black college-educated women. I find that none of the changes in Z^{IJ} had a comparably large positive impact on Black college-educated women's welfare gain, relative to the case of Black college-educated men.

Specifically, while Black college-educated women benefitted from the increase in the joint surplus from marrying White college-educated men (shown by $Z^{WhiteCG,BlackCG}$ in Table 1.6), this positive gain is *much lower* than what Black college-educated men experienced from marrying White women. These gender differences in the gains from marriage with non-Blacks are consistent with the anecdotal evidence that Black women face higher barriers in marrying out than Black men due to social pressures (Banks, 2012) and discrimination in the dating market (Stewart, 2020). My findings show that the gender differences in improvement in racial attitudes made substantial negative impact on Black women's welfare in the marriage market.

Another notable result in Table 1.6 is that the increase $Z^{BlackCG,WhiteCG}$, which is the marital surplus for Black college-educated men and White college-educated women pair, had a negative effect on Black college-educated women. This captures the general equilibrium nature of the effects from marital surplus changes. While increase in $Z^{BlackCG,WhiteCG}$ is a positive effect for college-educated Black men, it is a negative effect for college-educated Black women. This shows that the unbalanced improvement in marital surplus attached to interracial marriage leads to a gender gap in the gains from interracial marriage.

Table 1.6: Decomposition: Top three contribution from changes in **Z**, Black CG Women

		(1)	(2)	(3)
Contribution	Top (+)	2.0	1.9	1.2
		$Z^{WhiteCG,BlackCG}$	$Z^{BlackCG,BlackCG}$	$Z^{BlackSC,BlackCG}$
	Top (-)	-1.0	-0.9	-0.5
		$Z^{BlackCG,BlackSC}$	$Z^{BlackCG,WhiteCG}$	$Z^{BlackCG,BlackHSG}$

Notes: This table presents the top three positive and negative contributions from marital surplus to the 1980-2019 changes in the welfare gains from marital desegregation for Black college graduate women. For marital surplus Z^{IJ}, I refers to husband's type and J refers to wife's type.

I also find that none of the changes in the marital surplus had a large positive effect for Black high school graduate men and women, which are presented in Appendix Tables A.3 and A.4. These results confirm that among Blacks, the structural changes in the marital surplus have only been favorable to most educated Black men.

1.6.2.3 What drove the rise in welfare gains for White college-educated men?

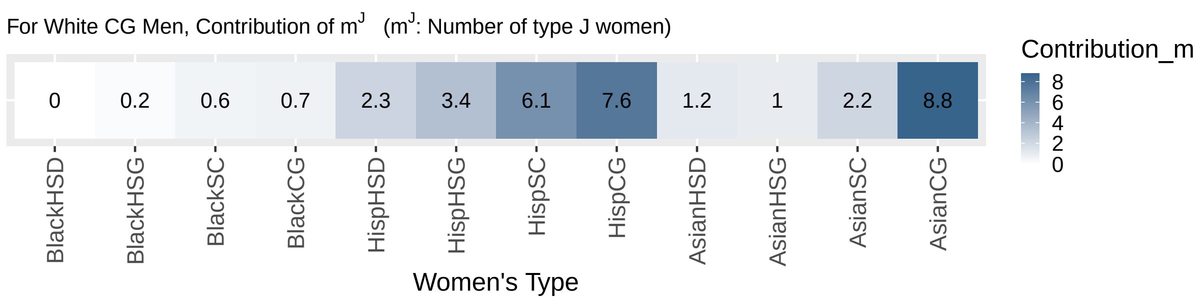
Recall that the increase in White college-educated men's welfare gain is driven by the overall population changes, as shown in Table 1.4. To understand which population changes played the largest role, I first decompose the population contribution into the ones made by (i) different-race female population, (ii) different-race male population, (iii) same-race female population, and (iv) same-race same male population. Table 1.7 shows that the positive contribution is mostly driven by the changes in different-race female population. This contribution is large enough to completely offset the negative contribution from the changes in different-race male population, who are the competitors to White men in the desegregated marriage market.

Table 1.7: Contributions from population changes to welfare gains for White CG men

	Contribution from Population			
	Diff-Race Female	Diff-Race Male	Same-Race Female	Same-Race Male
WhiteCG Men	34.1	-26.3	-5.0	4.0

Notes: This table presents the decomposition of the 1980-2019 changes in the welfare gains from marital desegregation for White CG men. This table focuses on the contributions from the population changes. Each column shows the summation of all contributions made by populations corresponding to the label.

Figure 1.5: Details on the contributions from the changes in different-race, different-sex population



Notes: This figure presents the decomposition of the 1980-2019 changes in the welfare gains from marital desegregation for White CG men. This figure focuses on the contributions from the changes in different-sex different-race population for White CG men. Each column shows the contribution made by the change in the corresponding population.

Figure 1.5 further reveals that the rise in the number of Asian college-educated women and Hispanic college-educated women made the largest positive impact on White college-educated men's welfare gain over the past decades. The implication of these results is that the rise in the welfare gains over time for White college-educated men was a mechanical consequence from the increase in the college-educated Asian and Hispanic population, rather than from the increase in the value of interracial marriages.

1.6.2.4 Why did the gains for White high school graduate men not increase over time?

One notable finding from Table 1.4 is that White high school graduate men had a large negative total contribution from the changes in marital surplus. To further investigate this, I present top three positive and negative contributions from the changes in marital surplus. Table 1.8 shows that the largest negative contribution is from the change in $Z^{WhiteHSG,HispHSG}$, which is the marital surplus between White high school graduate men and Hispanic high school graduate women. The magnitude of this contribution is more than twice time larger than other top contributing factors.

Table 1.8: Decomposition: Top three contributions from **Z**, White HSG Men

		(1)	(2)	(3)
Contribution	Top (+)	1.0 $Z^{WhiteHSG,WhiteHSG}$	0.8 $Z^{WhiteHSG,WhiteSC}$	0.8 $Z^{HispHSG,WhiteHSG}$
	Top (-)	-2.7 $Z^{WhiteHSG,HispHSG}$	-1.4 $Z^{WhiteSC,WhiteHSG}$	-1.0 $Z^{WhiteHSG,HispHSD}$

Notes: This table presents the top three positive and negative contributions from the 1980-2019 changes in marital surplus to the 1980-2019 changes in the welfare gains from marital desegregation for White HSG men. For marital surplus Z^{IJ}, I refers to husband's type and J refers to wife's type.

Recall that $Z^{WhiteHSG,HispHSG}$ has decreased over the past four decades as documented in Table 1.1. Hence, this result implies that the declining joint surplus from marriage with lower-educated Hispanic women is a part of the reason behind the lack of growth in welfare gains for lower-educated White men. This finding is consistent with Lichter, Carmalt, and Qian (2011) who suggest that the recent influx of new Hispanic immigrants has provided more same-race potential partners for Hispanics, especially for the lower-educated people, so that it slowed the process of marital assimilation among lower-educated Hispanics.

1.6.2.5 What drove the rise in welfare gains for White women?

Lastly, I examine the drivers of the increases of welfare gains for White women. First, for White college-educated women, I decompose the population contribution into the ones made by

(i) different-race male population, (ii) different-race female population, (iii) same-race male population, and (iv) same-race female population. Table 1.9 shows that, unlike the case of White college-educated men, White college-educated women did not benefit as much from the changes in different-race different-sex population. The positive contribution from the changes in the different-race male population is not large enough to completely offset the negative contribution from different-race female population, who are the competitors to White women in the desegregated marriage market.

Appendix Figure A.5 further confirms that White college-educated women did not benefit as much from the increase in Asian and Hispanic college-educated population. This implies that the reversal of the gender gap in college education as documented in Section 1.2 explains the gender differences in the contribution made by population changes to the welfare gain.

Table 1.9: Contributions from population changes to welfare gains for White CG women

	Contribution from Population			
	Diff-Race Male	Diff-Race Female	Same-Race Male	Same-Race Female
WhiteCG Women	25.7	-26.8	-4.5	5.5

Notes: This table presents the decomposition of the 1980-2019 changes in the welfare gains from marital desegregation for White CG women. This table focuses on the contributions from the population changes. Each column shows the summation of all contributions made by populations corresponding to the label.

Why the changes in marital surplus have overall positive effects on White women's welfare gains is less clear. Further investigation in Appendix Figure A.6 shows that there is no single large driver among the changes in marital surplus, but it is rather a combination of small equilibrium effects from multiple changes in the marital surplus that lead to the overall positive effects for White women.

1.6.3 Discussion

Decomposition results reveal that the underlying reasons for unequal gains from marital desegregation are complicated: some groups have gained from population changes, while other groups gained from marital surplus changes. A key finding is that the unbalanced marital surplus and unbalanced sex ratio lead to unequal gains from the access to interracial marriage. For example, while Black college-educated women did benefit from the increasing marital surplus from marrying White college-educated men, this benefit was not large enough and partly cancelled out by other negative forces, which includes the increase in the marital surplus of marriage between Black men and White women. For Whites, increasingly unbalanced sex ratio among college graduates, across all races, has substantially benefitted the marriage prospects of White men, while harming the marriage prospects of White women.

What do these results tell us about the progress of social integration in the US marriage market? My results show that not everyone benefits from the option of interracial marriage, if there is an unbalanced improvement in marital surplus or unbalanced sex ratio in the marriage market. In particular, Black women would not benefit from the option of interracial marriage, if there is a persistent gender gap in marital surplus for interracial marriage.

1.7 Simulating Complete Racial Integration

So far, I have shown how marital desegregation affected individual welfare and why the gains are unequal across groups. I now turn to a scenario of racial integration[23] : If there are less barriers to interracial marriage, how would it affect the probability of remaining single for each demographic group? I define *complete racial integration* as a scenario where race is no longer a factor considered in marriage matching. In this section, I perform counterfactual simulations to predict the effects of progress towards complete racial integration in the marriage market. I

[23]As discussed in O'Flaherty (2015), the term "integration" refers to a situation where groups of *equals* who cooperate with each other in mutually beneficial ways, which is different from the term "desegregation," which simply means removing legal barriers to intergroup contact.

describe the estimation procedures below.

Constructing the marital surplus for complete integration: To construct a trajectory towards the complete integration, I first construct a marital surplus matrix for complete racial integration. Note that this is not straightforward because by definition, any matrix that does not depend on race of each spouse can reflect complete racial integration. In practice, I choose a marital surplus matrix that (i) only depends on education of both spouses and that (ii) minimizes the weighted Euclidean distance from the estimated $\hat{\mathbf{Z}}_t$.

For clarity, I rewrite the marital surplus Z_t^{IJ} as $Z_t^{(R_i,E_i),(R_j,E_j)}$, where R_i (resp. R_j) denotes husband's (resp. wife's) race and E_i (resp. E_j) denotes husband's (resp. wife's) education. Then, the marital surplus for each education pair is constructed as the weighted average of estimated $\hat{Z}_t^{IJ}$ from the data, conditional on education levels of both spouses:

$$\hat{Z}_t^{E_i,E_j} = \sum_{R_i,R_j} \widehat{Pr}(R_i, R_j|E_i, E_j, t)\hat{Z}_t^{(E_i,R_i),(E_j,R_j)} \tag{1.18}$$

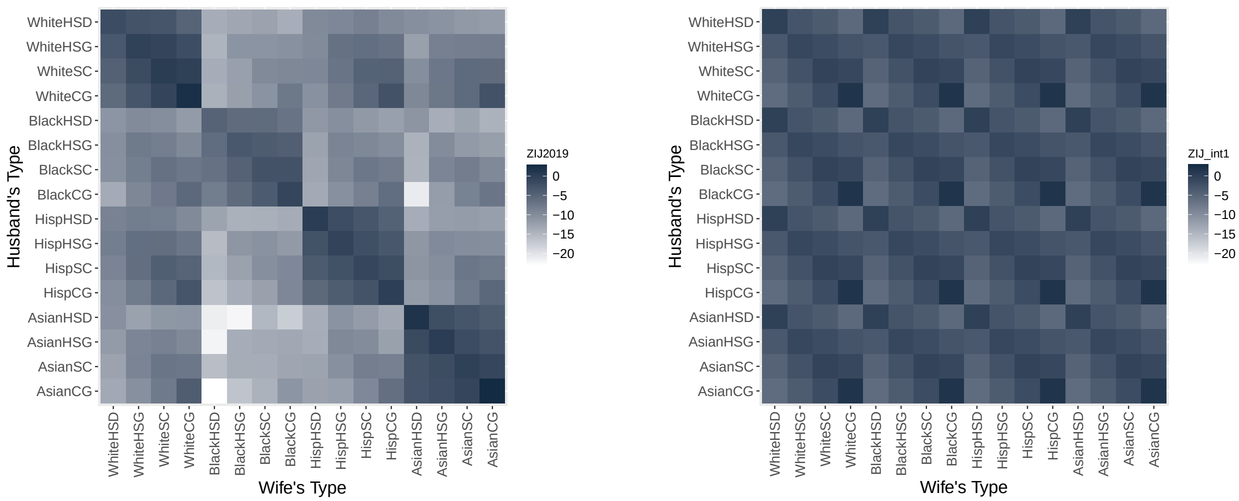
The marital surplus matrix for complete integration, denoted by $\hat{\mathbf{Z}}_t^{Integrated}$, is constructed by simply replacing all $\hat{Z}_t^{(R_i,E_i),(R_j,E_j)}$ in $\hat{\mathbf{Z}}_t$ with the corresponding $\hat{Z}_t^{E_i,E_j}$. Figure 1.6 visualizes the differences between the counterfactual marital surplus and the actual marital surplus.

To construct a trajectory of progress towards the complete integration, I take the following convex combination of the marital surplus matrices:

$$\hat{\mathbf{Z}}_t^{Simulated}(p) = (1-p)\hat{\mathbf{Z}}_t^{Actual} + p\hat{\mathbf{Z}}_t^{Integrated} \tag{1.19}$$

where $p \in [0, 1]$. This means that when p is closer to 0, the counterfactual marital surplus is closer to the actual marriage market. When p is closer to 1, the counterfactual marital surplus is closer to the case of complete racial integration.

Figure 1.6: Marital Surplus Matrix in 2019, Actual vs. Complete Integration



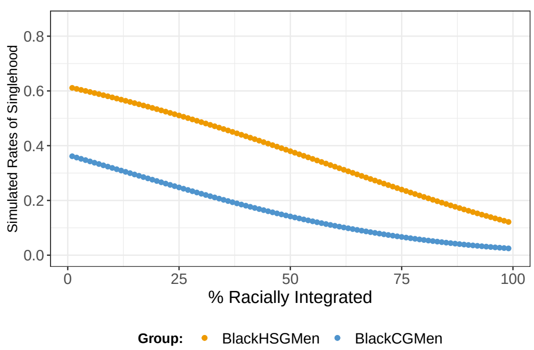
(a) Actual $\hat{\mathbf{Z}}_{2019}$ (b) Counterfactual $\hat{\mathbf{Z}}_{2019}^{Integrated}$

Note: This figure shows heatmap of the marital surplus Z_{2019}^{IJ} for the actual values that is estimated from data (Panel (a)) and the counterfactual values with complete integration (Panel (b)) and respectively. I refers to husband's type (Row) and J refers to wife's type (Column).

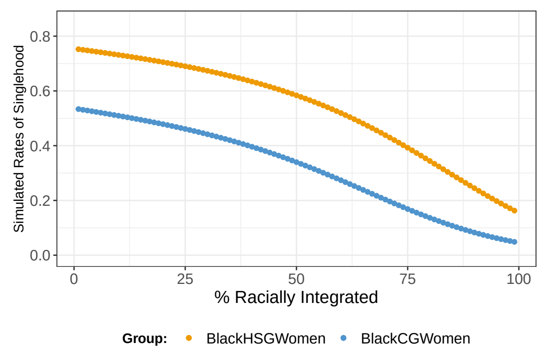
Computing the equilibrium rates of singlehood: For the survey year 2019, I compute the trajectory of the equilibrium single rates for each type of men and women as the world moves from desegregation to complete racial integration. This is done by estimating new equilibrium marriage patterns for each p, using the population vectors taken from data and the counterfactual marital surplus $\hat{\mathbf{Z}}_{2019}^{Simulated}(p)$ at each $p \in [0, 1]$ with interval 0.01. When presenting the results, I rescale p so that it represents the percentage of progress towards complete integration in the marriage market.

Figure 1.7 shows the simulation results for each group of men and women. I find that progress towards the complete racial integration would reduce the singlehood among Black men and women. 50% of racial integration in the marriage market would reduce the single rate of Black high school graduate women by 17 percentage points and reduce the single rate of Black college-educated women by 20 percentage points. Further progress towards the racial integration not only closes the racial gap in marriage but also makes Blacks marry more than Whites. In comparison, I find that racial integration would not change much the rates of singlehood among Whites at all stages.

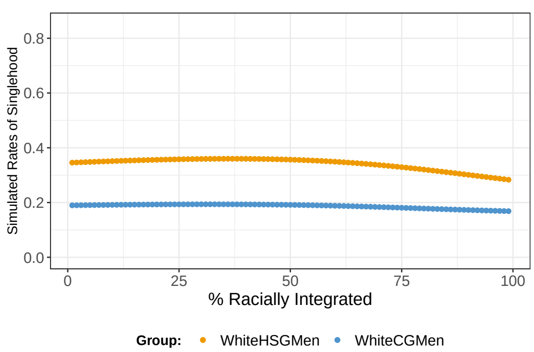
Figure 1.7: Simulated Rate of Singlehood for Varying Degree of Racial Integration



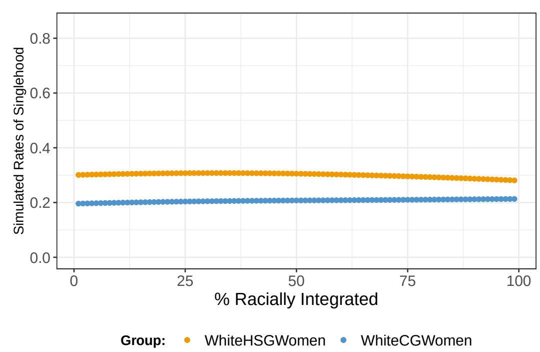
(a) Black Men



(b) Black Women



(c) White Men



(d) White Women

Note: This figure plots the simulated rate of singlehood at each % of racial integration (rescaled p) for the specified group. "% Racially Integrated" describes how close the counterfactual marital surplus is to the complete integration case. Estimation is done using the 2019 Census data. I focus on age 37-46 men and age 35-44 women. Further details on the sample restriction are described in Section 3.3.

These predictions show that racial integration would play an important role in improving the marriage prospects for Black men and women, who currently have low marriage rates, while not harming the marriage prospects for White men and women.

1.8 Conclusion

This paper investigates the interracial marriage rates for non-Hispanic Whites and Blacks in the US to understand: (i) who gained the most from interracial marriage, (ii) why some groups gain more than others, and (iii) how progress toward complete integration would affect marriage rates. The structural matching model enables me to define and estimate the welfare gains from marital desegregation. It also enables me to quantify the effects from various market-level changes on welfare gains across groups. This paper is the first to provide quantitative assessments to identify what drove unequal welfare gains from marital desegregation across different social groups.

The key finding is that the option of interracial marriage did not improve everyone's chances of getting married. In terms of why, the decomposition analyses show that the unbalanced improvement in marital preferences for interracial marriage substantially benefitted college graduate Black men, while not benefitting Black women as much. Moreover, increasing imbalance in sex ratio among college graduates across all races, benefitted White men, while hurting White women in terms of marriage rates. My findings have an important implication family formation not just in the US setting, but also in other countries where population is becoming more racially diverse and different groups may face different barriers to interracial marriage.

Simulation results show that progress towards racial integration would significantly increase the marriage rates among Blacks, without reducing the marriage rates of Whites. This finding suggests that the efforts toward improving racial relations could lead to better marriage prospects of Blacks, who currently have low My findings suggest two main avenues for future research. First, it is important to understand what drives the differing values of marital surplus across marriages. Marital surplus only reveals how the marital preferences differ across groups, but not *why*. For example, the matching model cannot distinguish why the marital surplus between Black men and

White women is higher than the marital surplus between White men and Black women. It would be helpful to further investigate whether these gender differences in marital surplus are affected by economic conditions, where people live, or other factors. Second, the question of which policies can promote interracial marriage needs to be further studied. Merlino, Steinhardt, and Wren-Lewis (2019) shows that greater racial diversity in high school increases the interracial dating as adults. It would be fruitful to study whether the policies that promote diversity in other settings, such as college, workplace, or residence, would increase interracial marriage and social integration.

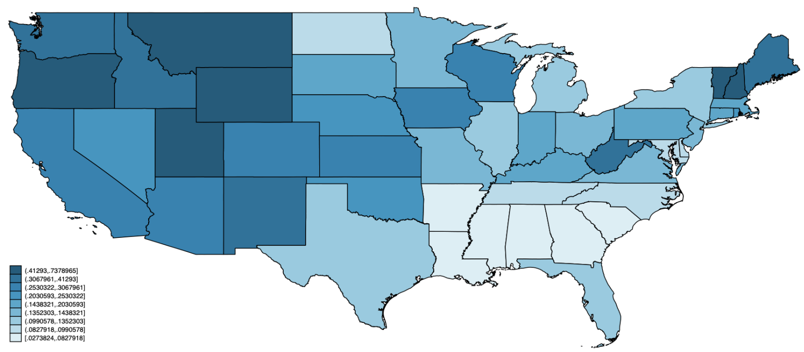
Chapter 2: Geographical Variation in Racial Sorting in the US Marriage Market

2.1 Introduction

Interracial marriage has steadily increased over time in the US. In 2019, 11% of married people aged 35 to 50 were married to partners of different races. However, there is a wide variation in interracial marriage across states. As of 2019, southern states such as Mississippi and Alabama exhibit interracial marriage rates as low as 5% of all marriages among Black people aged 35-50. In contrast, other states, such as California and Washington, exhibit interracial marriage rates as high as over 30% of all marriages among Black people. Because interracial marriage is often considered a barometer of social integration, these cross-state differences suggest that there may be a wide variation in racial attitudes across states.

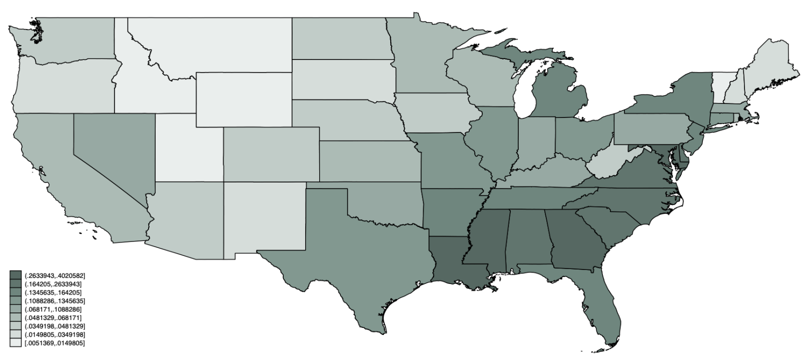
However, understanding the nature of spatial differences in interracial marriage patterns is a challenging task. Interracial marriage patterns are determined by both marital surplus and racial composition in each state, and it is difficult to disentangle the two. Consider an example of southern states. On the one hand, interracial marriage may be lower in southern states because the proportions of Black population in those states are higher than in others. As shown in Figure 2.2, there is a substantial geographical variation in the proportion of Black population, which is seemingly inversely proportional to the interracial marriage rate of Black people reported in Figure 2.1. This suggests that it may be mechanically more likely for Black women to meet and marry a Black man in a state where the Black population is high. On the other hand, the interracial marriage rate may be lower in southern states because the preference for interracial marriage is lower than in other states. It is well known that racial animosity is stronger in the Southern states than in others (Charles and Guryan, 2008), which may negatively affect the interracial marriage rates. Without using a theoretical framework that specifies what "preference for interracial marriage" means and an empirical framework to estimate it, it is difficult to examine the nature of geographical variation in interracial marriage patterns in the US.

Figure 2.1: Interracial Marriage, Among Married Black People, Age 35-50, 2019



Note: This figure shows the proportion of interracial marriage among married Black men and women aged 35-50 for survey year 2019. Data source is 2019 5% sample American Community Survey (2015-2019 5 year pooled sample). Survey weight is applied.

Figure 2.2: Proportion Black Population, Age 35-50, 2019



Note: This figure shows the proportion of Black population among all population aged 35-50 in each state. Data source is 2019 5% sample American Community Survey (2015-2019 5 year pooled sample). Survey weight is applied.

In this paper, I study geographical variation in racial assortative matching in the US marriage market from 1980 to 2019. I address the following questions. First, are there geographic variations in racial assortative matching? Second, are geographic disparities in racial assortative matching persistent over time? Third, how does racial assortative matching relate to racial attitudes in each state? Fourth, are individual welfare gains higher for all groups in states with low racial assortative matching?

To measure racial assortative matching, I use the same assortative matching index as Chiappori, Salanié, and Weiss (2017) and Chiappori, Costa Dias, and Meghir (2020). This index quantifies the tendency to marry within one's race after accounting for population distribution in each state. The underlying model behind this index is the transferable utility matching model with random preferences that is introduced by Choo and Siow (2006). The key idea of this model is that marriage sorting is determined by the structure of marital surplus from different types of marriage, where the type is defined by both husband's and wife's characteristics. Unlike the raw interracial marriage rates, the racial assortative matching index captures the preference for same-race marriage relative to different-race marriage. As discussed in Chiappori, Costa Dias, and Meghir (2020), racial assortative matching index is a local measure that depends on the pair of racial groups being considered. In order to understand how *individual-level* welfare from interracial marriage varies with racial assortative matching in each state, I follow the approach in Koh (2022). For each state, I measure the welfare gains from interracial marriage for each group of men and women to understand who benefits the most from lower racial assortative matching in each state.

Using the above methodologies, I find that there are substantial geographical variations in racial assortative matching even after accounting for differing population compositions across states. Specifically, in the survey year 2019, southern states, especially the ones in the "Deep South," exhibit higher racial assortative matching than others, and states in the West exhibit lower racial assortative matching among Black and White people. This geographic variation is more evident for people with some college education or more than for people without college education. In the survey year 1980, while the degree of racial assortative matching is much higher than in 2019 across all states, the geographic variation is similar to the one in 2019. This suggests that the geographic variation in racial assortative matching is persistent over the past four decades. I also show that geographic variation in racial assortative matching closely aligns with geographic variation in racial attitudes of White respondents of the General Social Survey, but not with the racial attitudes of Black respondents. This suggests that the geographic variation in racial assortativeness in marriage may be driven more by White people than Black people.

In terms of individual welfare gains from interracial marriage, I find that not everyone benefits from interracial marriage even in states with less racial assortative matching. Consistent with the national-level results in Koh (2022), I find that higher-educated Black men benefit more from interracial marriage than other Black men and women do across all states. However, even higher-educated Black men do not benefit from interracial marriage in the southern states, where racial assortative matching is higher than in other states. Black women, regardless of where they live, do not benefit at all from interracial marriage in terms of chances of getting married. This shows that the zero national-level gains from marital desegregation for Black women that are estimated in Koh (2022) holds across all states.

This paper is connected to the literature on assortative matching. I contribute to this literature by measuring geographic disparities in racial assortative matching in the US. Assortative matching index based on Choo and Siow (2006)'s framework has been used to study how assortative matching on various dimensions has changed over time. This includes educational assortative matching in the US (Chiappori, Salanié, and Weiss, 2017; Chiappori, Costa Dias, and Meghir, 2020) and educational assortative matching in Mexico (Hoehn-Velasco and Penglase, 2021). Most studies study marriage sorting at the national level, and studies on geographic variation in marriage sorting are still rare, with exceptions of Anderberg and Vickery (2021), Mourifié and Siow (2021), and Adda, Pinotti, and Tura (2022). My paper is most closely related to Anderberg and Vickery (2021) who use Choo and Siow (2006)'s and Mourifié and Siow (2021)'s frameworks to study how local social norm affects ethnic matching in the UK by using the regional demographic variation.

The rest of the paper is organized as follows. In Section 3.3, I describe the data that is used to estimate racial assortative matching indices and the data that is used to estimate racial attitudes across states. Section 2.3 describes the construction of racial assortative matching index. Section 2.4 shows the results for racial assortative matching across space, across education-level, and over time. It also discusses how geographic variation in racial assortative matching closely aligns with racial attitudes of White people. Section 2.5 presents the results for geographic variation in welfare gains from interracial marriage for different groups of men and women. Section 2.6 concludes.

2.2 Data

2.2.1 US Census

To capture marriage patterns for each year, I use Decennial Census data from 1980 to 2000, and 5-Year American Community Survey for the years 2010 and 2019, all of which are extracted from IPUMS (Ruggles et al., 2022). These datasets contain the largest sample sizes among the nationally representative household surveys in the US, which is crucial to properly capture the interracial marriage pattern for each state. The state reported by each household is based on where the household was located at the time of the survey.

I apply several sample restrictions. To estimate the matching model, the age range has to be restricted for both husband's and wife's sides. I select couples where wife is aged 35-50 and husband is aged 37-52. The lower bound of this age bracket is chosen to ensure most people have already made marriage decision. This is to avoid the truncation issue that young single men and women at the time of the survey may marry in the future. Two years of age gap between husband's age group and wife's age group reflects the fact that men tend to marry younger women, and the most common spousal age differences in the data are 1 and 2 years. Furthermore, I limit the sample to currently married couples and never-married singles. I do not include divorced people in the single sample to abstract away from the issues of selection into divorce. Survey weight is applied when computing marriage frequencies and population counts.

2.2.2 General Social Survey

To understand geographic variation in attitudes towards interracial marriage, I use General Social Survey (GSS) (Davern et al., 2021), which is a nationally representative survey in the US to measure opinions, attitudes, and behaviors. The GSS allows me to check whether the racial assortative matching index aligns with racial sentiment in each state. I use the data from 1980 to

2018 to construct proxies for the social acceptance towards interracial marriage.

There are multiple questions in the GSS that are related to racial sentiments. As discussed in Charles and Guryan (2008), the questions on racial sentiments may also reflect other dimensions of preference. For example, there is a GSS question on whether respondents believe that "racist books shouldn't be removed from public library." People with no feelings of racial animus may still respond positively to this question if they strongly favor freedom of speech. Given that the aim of this paper is to understand the preferences towards interracial marriage, I focus on the questions that are closely related to the sentiments about interracial marriage. To this end, I focus on two sets of questions. The first question asks: "Do you think there should be laws against marriages between Blacks and Whites?" This question was asked from 1972 to 2004 and ceased afterward. The second set of questions ask whether the respondent would oppose if a close relative marry a person from a certain race/ethinicity, which includes White, Black, Asian, and Hispanic. This set of questions is available from survey year 1988 onward. Responses range across five discrete scales from "strongly favor" to "strongly oppose." I rescale the responses so that the higher value corresponds to higher racial animosity.

The sample size of GSS is substantially smaller than that of the Census. The sample size is around 1,400 to 3,000 respondents for each survey year. To secure enough sample size to investigate the geographical variation in social acceptance towards interracial marriage, I limit the sample to all respondents whose age is between 25 to 70 at the time of the survey. The finest geographical level available is the census-designated region, which consists of New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific. Appendix Table B.1 provides a list of states for each census region.

2.3 Assortative Matching Index

I follow Chiappori, Costa Dias, and Meghir (2020)'s approach to measure racial assortative matching across the US states. This approach is based on the frictionless, transferable utility matching model with random preferences, which was introduced by Choo and Siow (2006). This model explicitly links the observed marriage patterns to the structural marital surplus from marriage with different types of partners. Marital surplus reflects economic and non-economic benefits from each type of marriage relative to singlehood. An assortative matching index based on any observed characteristics can be constructed using the structure of marital surplus.

In the model, each man (Mr. i) and woman (Ms. j) can choose to get married or remain single. Each marriage generates a surplus z_{ij} which is allocated between spouses. Under the assumption of perfectly transferable utility, the surplus is additively separable between spouses: $z_{ij} = u_i + v_j$. How the surplus is split between the spouses is determined by the marriage market equilibrium.

Each agent in the marriage market has characteristics that are observed and unobserved by the analyst. I denote I the observed type of Mr. i and J the observed type of Ms. j. In the context of this paper, the observed type for each agent is defined by his or her race and education level. The marital surplus can be expressed as:

$$z_{ij} = Z^{IJ} + \varepsilon_{ij} \tag{2.1}$$

where Z_{IJ} is a deterministic part of the surplus, and ε_{ij} is an idiosyncratic part of the surplus that reflects unobserved heterogeneity in marital preferences.

To identify Z^{IJ}, two assumptions must be imposed on the idiosyncratic part of the surplus. First is the *additive separability* assumption on ε_{ij}, which turns the idiosyncratic part into $\varepsilon_{ij} = \alpha_i^J + \beta_j^I$. Second assumption is on the distribution of random terms. Following the common practice in the literature, I assume that α_i^J and β_j^I are independent and distributed as type-1 extreme values. Under these assumptions, Choo and Siow (2006) show that the deterministic part of the marital surplus can be estimated using the following formula:

$$Z^{IJ} = ln\Big(\frac{Pr(Marry\ J|I)Pr(Marry\ I|J)}{Pr(Single|I)Pr(Single|J)}\Big) \tag{2.2}$$

Unlike raw marriage rates, Z^{IJ} captures the systematic gains from each type of marriage, which is independent of the population composition. Z matrix determines the equilibrium marriage patterns based on the observable characteristics.

Chiappori, Costa Dias, and Meghir (2020) show that an assortative matching index for any two distinct types I and K is constructed by taking the cross-difference of marital surpluses:

$$D^{II,KK}(Z) = Z^{II} + Z^{KK} - Z^{IK} - Z^{KI} \tag{2.3}$$

where first two components capture the marital surplus from same-type marriages and the last two components capture the marital surplus from different-type marriages. Higher $D^{II,KK}(Z)$ means that there are higher gains from same-type marriage, relative to different-type marriage. The assortative matching index is a *local* measure, meaning that it is defined for each combination of two types of matching traits. Therefore, the assortative matching can be high for one pair of observed traits, but low for other pairs.

2.3.1 Application to the US context

Because the goal is to estimate how racial assortative matching patterns differ across US states and over time, I define the marriage market for each state s in a given year t. Hence, the marital surplus is estimated for each state and year:

$$Z_{st}^{IJ} = ln\Big(\frac{Pr(Marry\ J|I)Pr(Marry\ I|J)}{Pr(Single|I)Pr(Single|J)}\Big|\ s,t\Big) \tag{2.4}$$

Similarly, assortative matching indices $D_{st}^{II,KK}$ are defined for each state and year.

When estimating the assortative matching index, I consider two different characterizations of the observed type of men and women in the marriage market. First, I consider the observed type given by ethinicity/race. There are four major races/ethnicities in the US, which are Non-Hispanic Whites, Black/African Americans, Hispanics, and Asians. Second, I consider the observed type given by ethnicity/race interacted with two education levels, which are (i) some college or more and (ii) no college education. This helps me understand whether racial assortative matching differs across education levels.

There are some cases where the sample size for certain observed types of men and women is too small in a given state. The small sample size may lead to an inaccurate measurement of racial assortative matching. To avoid this issue, I drop the states where there are less than 40 male respondents and 40 female respondents for each race that is used to construct each racial assortative matching index.

A limitation to keep in mind is that why marital surplus Z_{st}^{IJ} or assortative matching $D_{st}^{II,KK}$ varies across states and over time remains a black box without further modeling the drivers for the marital surplus. Nonetheless, these measures are still useful in understanding the evolution of racial assortative matching, which cannot be captured through raw marriage rates.

2.4 Racial Assortative Matching Across US States

As discussed in the previous section, the assortative matching index is defined for all different pairs of racial groups. To keep things manageable, I focus on presenting the results for racial assortative matching among Black and White men and women.

2.4.1 Geographical Variation in 2019

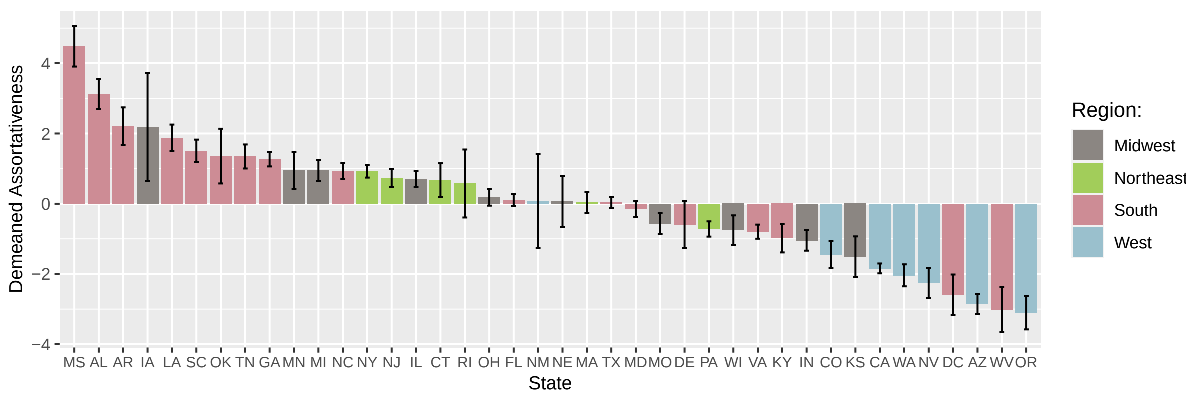
I first examine the racial assortative matching across the US states for the most recent time period, which is the survey year 2019. To focus on the relative position of each state in terms of racial assortativeness in marriage, I present the demeaned racial assortative matching index in a given survey year.[1] Figure 2.3 shows the racial assortative matching for Black and White racial groups for the survey year 2019. States are sorted from the highest to the lowest level of racial assortative matching. The results exhibit substantial geographical variation. The southern states exhibited the highest racial assortative marriage matching while the lowest were in the western states. Northeastern and Midwest states generally lie in the middle of racial assortative matching. The results confirm that even after accounting for the geographical variation in racial composition,

[1] Demeaning is done by subtracting the average value of racial assortativeness across states for the survey year 2019.

there are substantially different racial assortative matching among Black and White people across different states. Specifically, the high proportion of the Black population in the southern state (Figure 2.2) is not the only reason for the low interracial marriage rates of Black men and women as shown in Figure 2.1.

Notably, states in the "Deep South," which were most dependent on plantation and slavery before the American Civil War, show the highest racial endogamy even in 2019. The most common definition of Deep South consists of Alabama, Georgia, Louisiana, Mississippi, and South Carolina. All these states show substantial higher racial endogamy than other states, suggesting that racial relations remain more tense in these states.

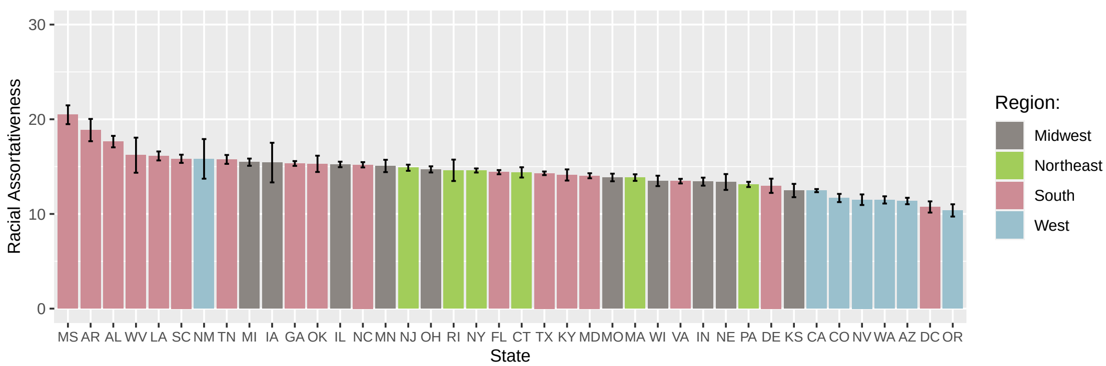
Figure 2.3: Demeaned Racial Assortative Matching Index, Black-White, 2019



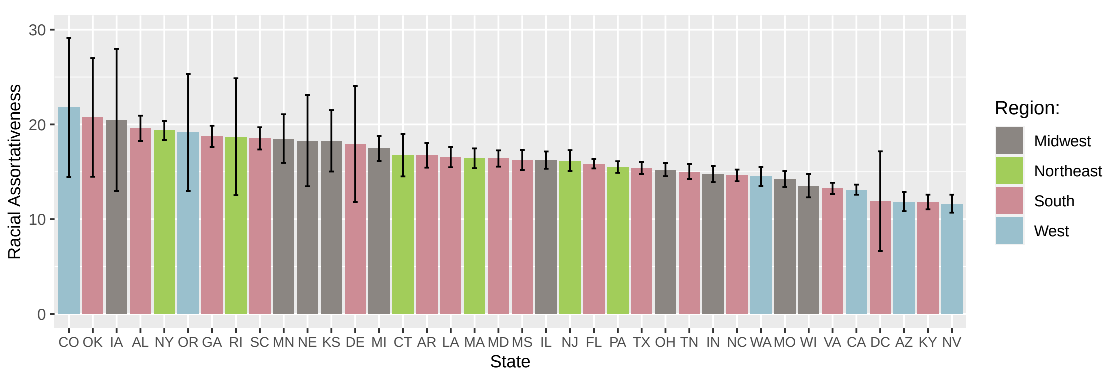
Note: This figure shows the demeaned racial assortativeness index $D_{st}^{BB,WW}$ for Black and White racial groups in each state for the survey year 2019. Data used to calculate these indices are 2019 5-Year ACS. I focus on age 35-50 women and age 37-52 men. Further details on the sample restriction are described in Section 2.2.1. 95% confidence intervals are calculated from the sampling variation in the data.

Racial assortative matching may differ across education levels. To understand this, I calculate the racial assortative matching among two different education groups: (i) some college or more and (ii) no college education. Figure 2.4 shows several findings. First, there are no clear differences in the levels of racial assortative matching across the two education levels. While the general level of racial assortativeness is slightly lower among people with some college education or more, the difference with the ones for the lower educated group is not large. Second, geographical variation in racial endogamy is more conspicuous among the higher-educated group than the lower-educated group. Panel (a) of Figure 2.4 exhibits similar geographical variation that is shown in Figure 2.3: Southern states, especially the Deep South, show the highest preferences for racial endogamy among higher-educated people, whereas the Western state have the lowest preferences for racial endogamy. In contrast, Panel (b) of Figure 2.4 shows that geographical variation is less clear among the lower-educated. For example, Southern states are more scattered across the ranks of racial endogamy. Moreover, Oregon, which shows the lowest racial endogamy in both Figure 2.3 and in Panel (a) of Figure 2.4, exhibits higher racial endogamy among people with no college education.

Figure 2.4: Racial Assortative Matching Index, Black-White, by Education, 2019



(a) Among Some College+



(b) Among No College

Note: This figure shows the racial assortativeness index $D_{st}^{BB,WW}$ for Black and White racial groups in each state for the survey year 2019. Data used to calculate these indices are 2019 5-Year ACS. I focus on age 35-50 women and age 37-52 men. Further details on the sample restriction are described in Section 2.2.1. 95% confidence intervals are calculated from the sampling variation in the data.

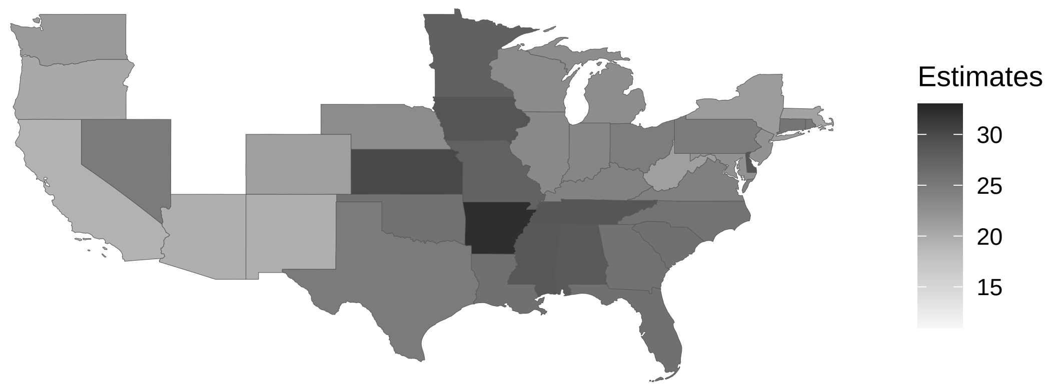
The racial assortative matching index is a useful measure to understand the geographic variation in same-race preference for marriage partners. Another interesting side of the picture is whether the marriage prospects for each demographic group are better or worse in the presence of lower racial assortative matching. This will be investigated in Section 2.5.

2.4.2 Persistence in Geographical Variation

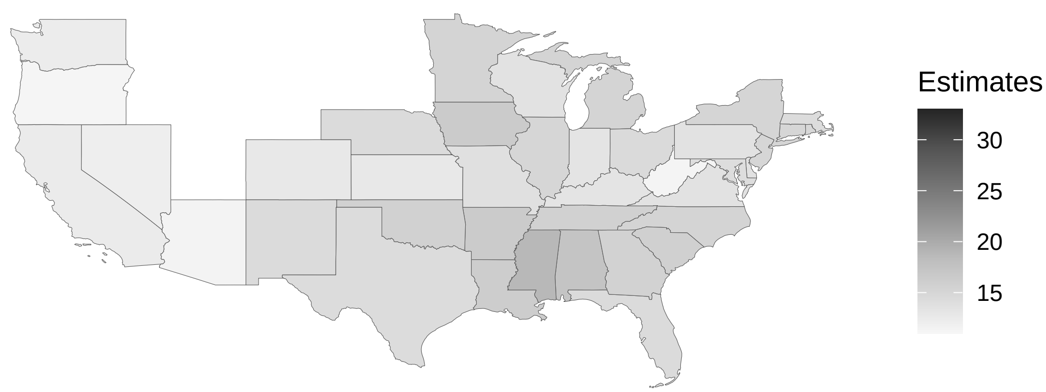
In this section, I investigate how racial assortative matching has changed over the past four decades for each state. The goal is to understand if geographical patterns in racial assortative matching remain persistent over time. Figure 2.5 shows the racial assortative matching indices for Black and White across states in 1980 versus 2019. To facilitate the comparison, I set the color scale the same for the two panels. The maps show several patterns, First, the shading of the map changed dramatically from 1980 to 2019. This shows that racial assortative matching has become much lower over the past four decades across all states. This is consistent with the observation that interracial marriage, while still uncommon compared to same-race marriages, has become much more prevalent over the past several decades.

Second, in terms of geographical variation, in 1980, the South and some northwestern states exhibited the highest racial assortative matching while the western states exhibited the lowest racial assortative matching. States in Deep South, including Alabama, Mississippi, and Louisiana particularly exhibited the higher racial assortative matching. The geographical pattern looks similar in 2019. To better understand the persistence of the geographic patterns, I examine whether a state's rank within the racial assortative matching distribution is stable over the time period. In Figure 2.6, I display a scatterplot of racial assortative matching across time periods. There is a strong positive relationship between racial assortative matching indices across time periods, suggesting that there is a persistent geographical variation.

Figure 2.5: Racial Assortative Matching Index, Black-White, 1980 vs. 2019



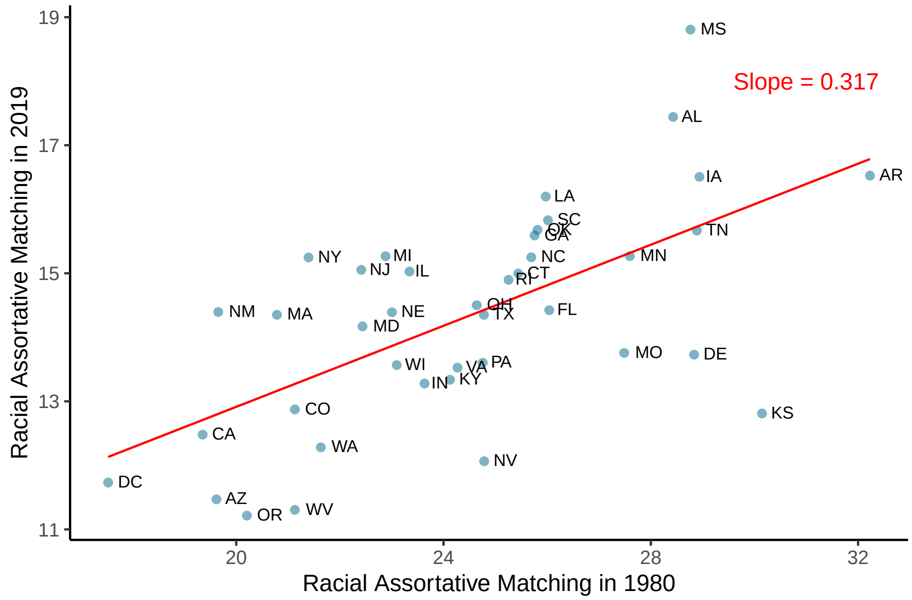
(a) 1980



(b) 2019

Note: This figure shows the racial assortativeness index $D_{st}^{BB,WW}$ for Black and White racial groups in each state. Data used to calculate these indices are 1980 Decennial Census for panel (a) and 2019 5-Year ACS for panel (b). I focus on age 35-50 women and age 37-52 men for each survey year. Further details on the sample restriction are described in Section 2.2.1. States with less than 40 respondents for Black men and women, respectively, are dropped from each map.

Figure 2.6: Persistence in Racial Assortative Matching Over Time



Note: This figure shows scatter plots of racial assortative matching across two time periods 1980 and 2019. States with less than 40 respondents for Black men and women, respectively, are dropped from the plot.

2.4.3 Relations to Racial Attitude

In this section, I investigate how closely the racial assortative matching index aligns with racial sentiments in each state. In General Social Survey (GSS), there is no consistent question for interracial marriage that was asked from 1980 to 2018. Therefore, as discussed in Section 2.2.2, I chose two different questions for the survey years 1980 and 2018. To secure enough sample size for each region for Black and White respondents, respectively, I use a pooled sample from 1980 to 1985 for the survey year 1980 and a pooled sample from 2014 to 2018 for the most recent survey year.

Table 2.1 summarizes patterns of racial sentiments related to interracial marriage across regions in the US. As described in Section 2.2.2, I rescale the responses so that higher values indicate higher racial animosity. Columns 1-2 show average responses within each race in each region during survey years 1980 to 1985 to the question on whether the respondent thinks there should be a law against Black-White marriage. There are two notable facts. First, the proportion of White respondents who favor the law against Black-White marriages is much higher than that of Black respondents across all regions except Mountain. This reflects that back in the 1980s, sentiment against Black-White marriage was much more negative for Whites than for Blacks. Second, the geographical variation in racial sentiment is similar to the racial assortative matching in 1980 that is presented in Figure 2.5. For Whites, the proportion who favored the law against Black-White marriage was highest in the South, ranging up to over 50% agreeing to this law in the East South Central (Alabama, Kentucky, Mississippi, and Tennessee). West exhibited the lowest proportion of White respondents favoring anti-miscegenation law. Similarly, the proportion of Black respondents agreeing with this statement is higher in the South than in the other regions, with exception of the Mountain region.

Table 2.1: Racial Sentiments Across Census Regions

	Favor law against Black-White marriage Survey years: 1980-1985		Oppose relative marrying other race Survery years: 2014-2018	
	(1) White Respondent	(2) Black Respondent	(3) White Respondent	(4) Black Respondent
New England	0.18	0.00	2.59	2.43
Middle Atlantic	0.22	0.01	2.66	2.38
East North Central	0.25	0.04	2.68	2.12
West North Central	0.26	0.04	2.46	1.90
South Atlantic	0.46	0.12	2.83	2.15
East South Central	0.52	0.10	2.98	2.05
West South Central	0.39	0.10	2.93	2.28
Mountain	0.15	0.20	2.61	2.39
Pacific	0.14	0.02	2.52	2.33
Overall mean	0.29	0.07	2.70	2.19
N	3911	694	2549	688

Notes: This table reports sample means for each of the census regions for corresponding years and respondents. Columns (1) and (2) are for the question "Do you think there should be laws against marriages between Blacks and Whites?" Column (3) is for the question "How much do you oppose to your close relative or family member marrying a Black person?" Column (4) is for the question "How much do you oppose to your close relative or family member marrying a White person?" Sample is limited to respondents aged 25-70 at the time of the survey.

Columns 3-4 of Table 2.1 show average responses within each race in each region during survey years from 2014 to 2018 to the question on whether the respondent would be opposed if his or her close relative or family member marry a person from a different racial group, which can be White, Black, Hispanic, and Asian. To focus my attention on sentiments related to Black-White marriage, I tabulate the responses for marrying a Black person for White respondents and the responses for marrying a White person for Black respondents. The responses range across five scales, where 1 corresponds to “Strongly Favor" and 5 corresponds to “Strongly Oppose."

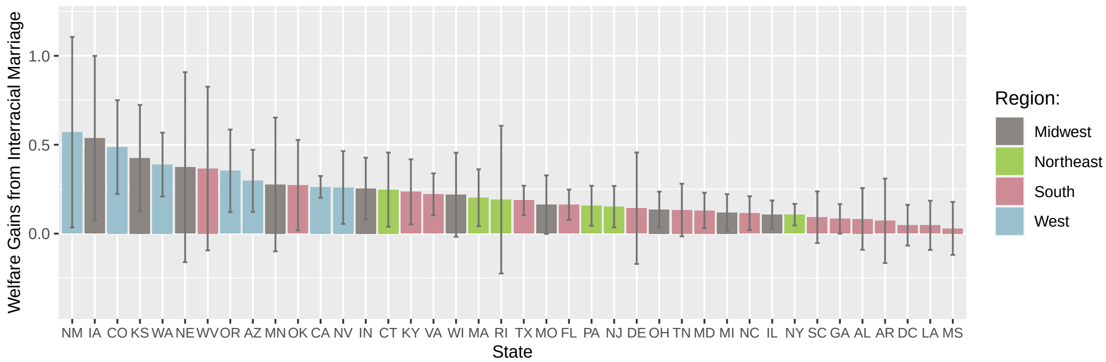
Results show that overall more White respondents oppose their close relatives marrying a Black person than Black respondents do regarding their close relatives marrying a White person. Regarding the geographical variation in racial sentiments, the responses from White people closely reflect the geographical variation in racial assortative mating in the survey year 2019 (Figure 2.3). Responses from White respondents in the South exhibit more negative attitudes towards Black-White marriages, and the Pacific shows on average more positive racial acceptance. However, such geographical patterns are not shown for Black respondents. In fact, the average responses for the statement for Black respondents in the South exhibit more positive racial acceptance than the responses from other regions including the Pacific, New England, and Middle Atlantic. Recall that the racial assortative matching index quantifies the overall preferences to marry within one's race, but it cannot distinguish which party is driving the racial assortative matching. The results from General Social Survey suggest that higher racial assortative matching in the Southern state may be driven more by White people's marital preferences than by Black people's.

2.5 Geographical Variations in Individual Gains from Interracial Marriage

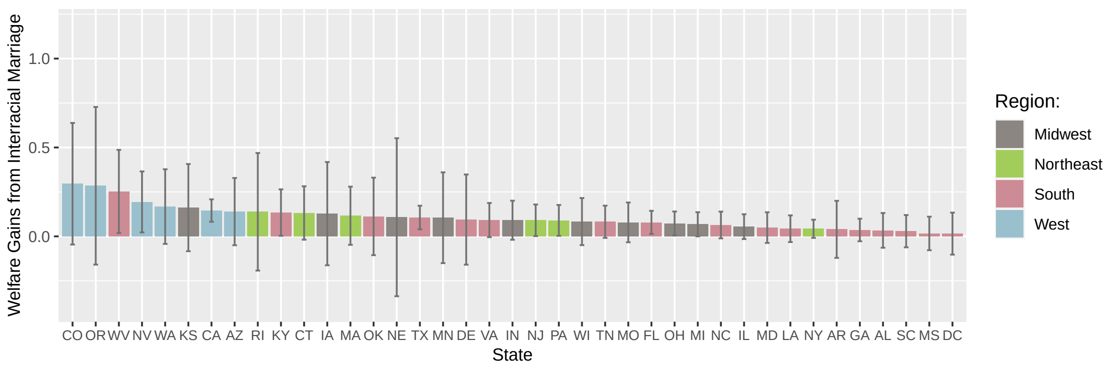
So far, I have shown that there are substantial geographical variations in racial assortative matching even after accounting for the demographic composition of each state. While this measure is useful in quantifying the preference for marrying within one's race, racial assortative matching does not reveal anything about individual welfare from lower racial assortative matching. In my companion paper (Koh, 2022), I quantify the individual welfare gains from interracial marriage and showed that college graduate Black men have increasingly benefited from interracial marriage than their lower-educated male counterparts and female counterparts. I also show through simulation exercises that if marital surplus did not depend on race anymore (i.e. no racial assortative matching), minority groups substantially benefit from the so-called “complete racial integration" in the marriage market. In this section, I examine the geographical variation in the individual welfare gains from interracial marriage and relate the estimates to racial assortative matching from Section 2.4.

To measure the welfare gains from interracial marriage for each group in each state, I follow the same approach as in Koh (2022), which is discussed in detail in Chapter 1 of this dissertation. The idea is to compare (i) the individual welfare in the current marriage market where interracial marriage happens with (ii) the individual welfare in the counterfactual marriage market where everything else is the same but interracial marriage is not allowed. With the type-I extreme value distributional assumption on the random marital preferences, the individual welfare in the marriage market is fully summarized by the probability of remaining single for each group. Therefore, welfare gains from interracial marriage essentially captures how much a certain group is more likely to get married in the actual marriage market, relative to a counterfactual marriage market where interracial marriage is not allowed.

Figure 2.7: Welfare Gains from Interracial Marriage, Black Men, 2019



(a) Some College+ Black Men

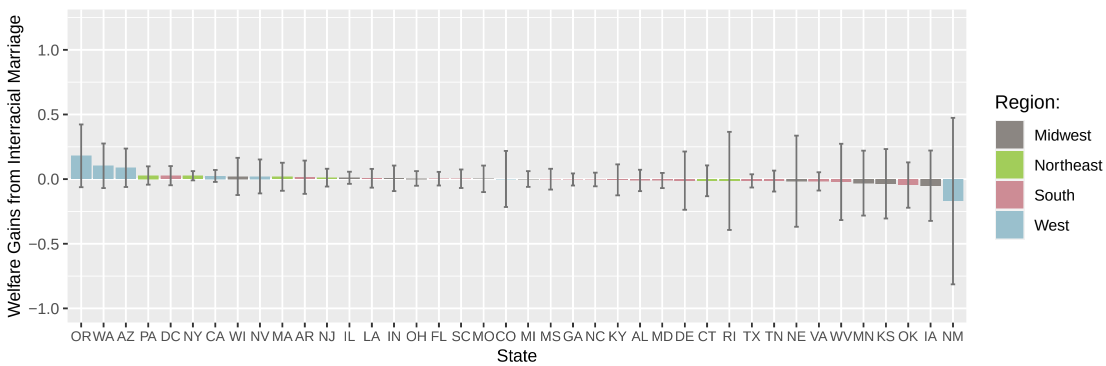


(b) No College Black Men

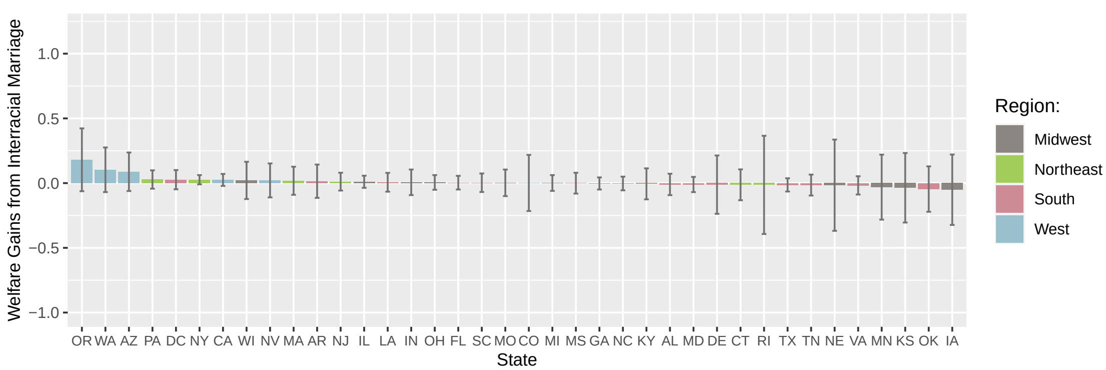
Note: These figures plot the welfare gain from marital desegregation following the approach in Koh (2022) for each specified type of men in each state. Data used to calculate the gains are 2019 5-Year ACS. Further details on the sample restriction are described in Section 2.2.1. Shade for each line refers to the 95% confidence interval. Standard errors are calculated from the sampling variation in the data.

Figure 2.7 plots the welfare gains from interracial marriage for Black men in the survey year 2019. Consistent with the national level results reported in Koh (2022), higher-educated Black men gain more from interracial marriage than their lower-educated male counterparts. There is a clear geographical variation in the welfare gains from interracial marriage. As shown in Figure 2.7a, Black men with some college education or more who live in Western states gain more from interracial marriage. Those who live in the Southern states, especially the Deep South, have small and statistically insignificant gains. Figure 2.7b shows that welfare gains for Black men without any college education are not statistically significantly positive for most states, with an exception of California and Texas. Nonetheless, the geographical pattern in the mean welfare gains is similar to that of higher-educated Black men. The geographical variation in individual welfare gains from interracial marriage for Black men is similar to the one in racial assortative matching that is reported in Figure 2.3. Black men gain from interracial marriage in states where racial assortative matching is lower, and even the higher-educated Black men do not benefit from interracial marriage in the Deep South.

Figure 2.8: Welfare Gains from Interracial Marriage, Black Women, 2019



(a) Some College+ Black Women



(b) No College Black Women

Note: These figures plot the welfare gain from marital desegregation following the approach in Koh (2022) for each specified type of women in each state. Data used to calculate the gains are 2019 5-Year ACS. Further details on the sample restriction are described in Section 2.2.1. Shade for each line refers to the 95% confidence interval. Standard errors are calculated from the sampling variation in the data.

Figure 2.8 plots the welfare gains from interracial marriage for Black women in the survey year 2019. Unlike the case of Black men, Black women receive zero welfare gain from interracial marriage across all states. Even in the states with lower racial assortative matching like the West, interracial marriage does not improve Black women's chances of getting married. This result implies that Black women are racially segregated in the marriage market regardless of their education level and where they live. This shows that not everyone benefits from interracial marriage even in states where racial assortative matching is low.

2.6 Conclusion

This paper investigates the geographical variation in racial assortative matching across states and over time. I document several new facts. First, preference for same-race marriage compared to different-race marriage is the highest in the southern states and the lowest in the western states, even after controlling for the demographic composition. Second, the ranking of each state in terms of racial assortative matching has been persistent over the past four decades. Third, the geographic variation in racial assortative matching is closely related to the racial attitudes of White respondents, but not of Black respondents. Specifically, General Social Survey results reveal that Black people in the South do not have lower acceptance towards Black-White marriage than Black people in other states. This suggests that geographic variation in racial assortative matching may be driven more by White people's marital preferences than by Black people's marital preferences. In terms of individual welfare gains from interracial marriage, I find that higher-educated Black men living in the West benefit more from interracial marriage and those living in the South do not benefit at all from interracial marriage. This is consistent with the geographical patterns in racial assortative matching. On the other hand, Black women do not benefit at all from interracial marriage regardless of where they live.

Measuring racial assortative matching in each state is an important step in understanding the geographic variation in racial marital preferences. However, what drives the geographic variation remains to be studied. General Social Survey results show that racial attitudes of White people may play a crucial role in determining geographic patterns in racial assortative matching. It would be helpful to further investigate whether geographic variation in racial segregation in various dimensions, such as schools, workplaces, and residences, affect racial sorting in the local marriage market. This is left for future work.

Chapter 3: Spousal Bargaining Power and Consumption of Married Couples in the US: Evidence from Scanner Data

This chapter was co-authored with So Yoon Ahn (University of Illinois at Chicago).

3.1 Introduction

There is substantial evidence from the developing country settings that bargaining power within household affects household decision-making in consumption. For example, unearned income in the hands of wives results in healthier food consumption (Thomas, 1990; Attanasio and Lechene, 2014; Armand et al., 2020) and improved children's nutritional outcomes (Duflo, 2003). Other factors, such as marriage market conditions (Ahn, 2022) and women's age (Calvi, 2020), are also shown to affect whether households allocate more expenditure to female-exclusive goods. However, there is a lack of evidence on whether the bargaining power between spouses affects household consumption in the developed economies, where gender inequality still exists but is less pronounced than in the developing countries.

In this paper, we study the impacts of spouse bargaining power on household consumption patterns of married couples in the United States, using a detailed, barcode-level expenditure data from 2004 to 2017.[1] We use two proxies for spouse bargaining position in the household. The first proxy is the relative education level between two spouses, which is a commonly used distribution factor[2] in the intrahousehold bargaining literature. However, using spouse relative education as a

[1]Researchers' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

[2]"Distribution factor" refers to any variable that affects the decision process of households but does not influence preferences or budget constraints.

distribution factor may have endogeneity issues, because couples do not match randomly. Couples with similar education level may have different consumption preferences compared to those who marry someone with different education level. To alleviate this issue, we construct the second proxy of spouse bargaining power – the relative potential wages of women to men, which exploits plausibly exogenous labor demand shocks for industries that are largely segregated by gender. Our measure of relative *potential* wage is, to the best of our knowledge, a novel distribution factor that has not been used in the literature, and this is our preferred distribution factor in our analyses.

Previous literature on family economics shows that relative earnings are important determinants of bargaining power within households.[3] Most of existing studies use *household-level* relative observed earnings as a measure of bargaining power within households. Although household-level relative earnings are likely to reflect bargaining powers, using them in the demand equations posits methodological concerns because relative earnings may be correlated with unobserved preference heterogeneity. For instance, relative preferences for clothing may be correlated with relative tastes for working. If this is the case, we would see a positive correlation between relative earnings and relative demands for clothing. However, this is a spurious correlation and not a bargaining power impact.

To overcome these potential endogeneity concerns associated with using household-level relative wages, we construct a Bartik-style *market-level* relative potential wages of women. This measure exploits the fact that men and women have been more dominant in different industries (e.g., construction for men and service industries for women). We create sex-specific local wages based on the industrial composition of the county and state-level wage growth. This allows us to separate the effects of relative wages and underlying worker characteristics in the county, which could be correlated with consumption patterns. In contrast to studies that focus on shocks to specific industries (Kearney and Wilson, 2018; Autor, Dorn, and Hanson, 2019), our Bartik-style approach

[3]Conditional on total family income, the source of income (or relative income) should not matter in determining household allocations if households behave as if it is a unitary entity. However, this income pooling hypothesis has been numerously rejected, supporting the collective approaches where husbands and wives may have different preferences and bargaining power affects final allocations.

utilizes wage variation across all industries and across all states, which is similar to the approaches in Aizer (2010) and Shenhav (2021). Our paper adds to the growing evidence that gender-relative labor market shocks affect family outcomes, such as domestic violence (Aizer, 2010; Erten and Keskin, 2021), marriage or fertility (Autor, Dorn, and Hanson, 2019; Kearney and Wilson, 2018; Shenhav, 2021), and spouse quality (Shenhav, 2021). In contrast to previous studies focusing on relatively high-stake rare events, we focus on daily decisions which have implications on a broader set of populations.

We use Nielsen Consumer Panel Data from 2004 to 2017 to measure consumption patterns of households in the US. Nielsen dataset have several benefits relative to typical consumer expenditure surveys. Household expenditure surveys generally do not have information on where the purchase was made and are aggregated to rather large consumption categories (e.g., beef) without details of the products. In contrast, Nielsen dataset have the UPC-level information as well as the detailed information on the frequency of purchases and the stores where the purchases were made. This helps us understand the impacts on consumption patterns in detail and mechanisms at play. Moreover, we can identify various gender-exclusive goods using detailed product information.

Our current results find that both higher wife's education relative to husband's and higher female-to-male wage ratio affect household budget shares of married couples in a way that is more favorable to wives. We first present results using the difference between wife's and husband's years of education, fixing husband's education level. We find that higher wife's education relative to husband's is associated with a larger expenditure share on health and beauty goods, a smaller expenditure share on alcohol and tobacco, and a larger budget share on books, stationary, and school supplies. These effects are all statistically significant at the 1% level. Because our descriptive analyses show that single women allocate significantly more budget on beauty items and single men allocate significantly more budget on alcohol, we interpret these results as a higher relative female education shifting household budget share more favorable to wives.

Using relative potential wages also results in similar findings that are consistent with the bargaining power story. We show that a rise in gender wage ratio significantly increases the budget share on beauty and significantly decreases the budget share on alcohol. These results are statistically significant at 5% level, after controlling for a rich set of individual-level controls and fixed effects. For food consumption, although the effects are not statistically significant with the current categorization of food items, we find that the higher gender wage ratio seem to increase food budget on frozen food.[4] We also find results that are potentially related to child investment. We find that households allocate more on books, stationary, and school supplies when female-to-male wage ratio rises. When dividing our sample into couples with children and couples without children, we find that the statistically significant positive effect on books, stationary, and school supplies consumption is only found for couples with children.

We investigate potential mechanisms which may explain the results other than the bargaining power channel. One potential channel that explains the results is the total income effect because relative earnings gap may affect total household earnings. We rule out this channel by showing that the gender wage ratio does not affect household income or total household expenditure. Another potential channel is changes in labor supply of husbands and wives. This channel can be particularly important to understand the impacts on food consumption. We plan to investigate this channel more in depth in the future. We also show that both the relative potential gender wage and the opposite gender potential wage do not have statistically meaningful effects on any of the consumption outcomes for single individuals living alone. This strengthens the interpretation that the relative wage only matters for the consumption of couples.

To further understand the impacts of relative wages on household bargaining, we estimate how relative wage ratios affect a sharing rule, how married couples split household resources, using a structural model. Specifically, we use a collective household model and rely on identification results from Chiappori, Fortin, and Lacroix (2002) which allow us to recover the partial of the sharing rule with respect to relative female wages. We find that a standard deviation increase in relative female wages leads to an increase of 63.7 dollars in wives' shares. The size of the impact should be understood in the context of expenditure; this change is computed out of average

[4] We plan to investigate the effects of gender wage ratio on food consumption using more detailed food categories.

total annual household expenditure of \$4,025 on Nielsen-tracked items.[5] As such, the seemingly small amount corresponds to 1.6% of total Nielsen expenditures, which is a significant change. This estimate shows that changes in labor market conditions favorable to women influence overall household allocations so that women control more resources within households.

3.2 Conceptual Framework

Over the past 30 years, it has been widely shown that households do not behave as a unitary entity for making economic decisions such as labor supply or consumption. The unitary household model assumes that households have a single representative utility function under a common budget constraint, which is obtained by pooling the incomes of every household member. The income pooling hypothesis from the unitary assumption has been rejected from numerous empirical studies (Browning, Chiappori, and Weiss, 2014).

The collective model approach makes a more realistic assumption that multiple agents within households may have different preferences. It assumes that household bargaining leads to Pareto-efficient allocations—meaning that no other feasible choice would have been preferred by every household member. This cooperative model assumption is likely to hold for married couples who know each other's preferences well and interact on a regular basis.[6] We introduce the baseline collective model here and explain how this model relates to our empirical setting.

Suppose that there are two members of the household, h (husband) and w (wife). The household utility can be represented as follows:

$$u^H(\mathbf{Q}, \mathbf{q}, \mu(\mathbf{P}, \mathbf{p}, x, \mathbf{z})) \quad = \quad \max_{\mathbf{q_h}, \mathbf{q_w}} \{u^h(\mathbf{Q}, \mathbf{q^h}) + \mu(\mathbf{P}, \mathbf{p}, x, \mathbf{z}) u^w(\mathbf{Q}, \mathbf{q^w})\}$$

subject to $\mathbf{q^h} + \mathbf{q^w} = \mathbf{q}$. $\mathbf{Q}$ and $\mathbf{q}$ indicate the vectors of public goods and private goods. $\mathbf{q^h}$ and $\mathbf{q^w}$

[5]Nielsen is focused mostly on frequently purchased, grocery-related items.

[6]There is another class of household decision models which is based on non-cooperative assumptions. Refer to Lundberg and Pollak (1993) for "separate spheres" models. For these models, allocations within marriage are characterized by a non-cooperative Nash equilibrium.

are private goods for husbands and wives, respectively. x is the total household expenditure. $\mathbf{z}$ is a vector of distribution factors. Distribution factors are variables which affect decision process but do not affect preferences or budget constraints. $\mu(\mathbf{P}, \mathbf{p}, x, \mathbf{z})$ is Pareto weight and can be interpreted as relative *power* of the wife. This Pareto weight determines the optimal allocation among the outcomes characterized by the Pareto frontier. The household budget constraint is given as follows:

$$\mathbf{P}'\mathbf{Q} + \mathbf{p}'(\mathbf{q^h} + \mathbf{q^w}) \leq x$$

Empirically, we do not observe Pareto weight μ. However, we can observe distribution factors which affect the outcomes only through the impacts on the Pareto weight. Such examples include relative income, relative age, sex ratios, divorce laws, and gender of the benefit's recipient.[7] If there is a change in a distribution factor, which is favorable to women (e.g., women become the recipient of benefits), Pareto weight increases and this leads to household allocation choices which favor women.

To understand the impacts of spousal bargaining power on consumption patterns of households, we consider two distribution factors which may affect consumption choices of households, as mentioned in the introduction. The first distribution factor is relative education, which has been extensively used as a proxy for bargaining power in the literature (e.g., Quisumbing and Maluccio (2003); Basu and Ray (2011); Schaner (2017)). If wife is more educated than husband, she may have more say in household decision-making process, including consumption. Previous literature suggests that higher relative education of wives matters for household decision making; for example, Calvo, Lindenlaub, and Uniat (2021) document that women who are at least as educated as their husbands receive a larger share of the household private consumption, using German socioeconomic panel. However, as Lewbel and Pendakur (2008) point out, one caveat associated with using relative education as a distribution factor is that it is often difficult to distinguish the pure (demographic) education impact from a relative education (distribution factor) impact.

[7]For detailed explanations on possible distribution factors, refer to Browning, Chiappori, and Weiss (2014).

The second distribution factor is gender-specific labor market conditions. Better labor market opportunities for women relative to men are likely to increase women's ability to extract more resources within the household. The previous literature has shown that relative incomes, wages, or earnings are important distribution factors which affect household consumption decisions (e.g., Browning et al. (1994), Thomas (1990)). However, if these measures are calculated at the household level, we face potential endogeneity challenges—relative income may be correlated with unobserved preference differences. To overcome this potential endogeneity issues, we construct a Bartik-style measure of female-to-male wage ratio at the county level which captures potential labor market opportunities for women and men, which we describe in Section 3.6. In previous literature, Aizer (2010) uses a similarly constructed Bartik female-to-male potential wage ratio in the US setting and shows that as female relative potential wage goes up, domestic violence goes down, which can be explained with women's increased bargaining power. However, the effects of gender-relative potential wage on household consumption in the US setting have not been examined in the literature.

3.3 Data

3.3.1 Consumption

For household consumption outcomes, we use the Nielsen Consumer Panel Data that spans from 2004 to 2017, which is made available by the Kilts Center of Marketing at the University of Chicago Booth School of Business. There are 40,000 - 65,000 households participating in the consumer panel each year. The sample is balanced on demographic characteristics to reflect the universe of household in the United States.

This dataset is suitable for our analysis due to the detailed nature of recorded consumption and large sample size. This data contains barcode-level information about the prices and quantities of purchased products that are recorded by the participating households after each shopping trip using in-house scanners. Because product information, price, and quantity of most products are accurately recorded by the in-house scanners, Nielsen dataset has more granular information than the conventional consumer survey datasets in the US (e.g. CEX and PSID) that record household consumption based on a retrospective memory.

Nielsen dataset records all purchases of barcode level products in 10 NielsenIQ food and non-food departments, which are (1) Health and Beauty Aids, (2) Dry Grocery, (3) Frozen Food, (4) Dairy, (5) Deli, (6) Packaged Meat, (7) Fresh Produce[8], (8) Nonfood Grocery, (9) Alcohol, and (10) General Merchandise. Appendix Table C.1 gives further description on what items are included in each of these departments. As long as purchased products are within these department categories, the purchases from all retail outlets (including department stores, grocery stores, convenience stores, and online stores) have to be recorded by the household. Products that are outside these department categories are not recorded in the scanner.[9]

In addition to departments, the purchases are categorized into approximately 100 product groups and approximately 1,000 product modules. In addition to these categories, UPC is recorded for all the purchases, which enables us to figure out exactly what was bought by each households. However, because the barcode-level consumption is too granular for us to investigate, we use aggregate goods, such as departments and clusters of product groups and product modules, for our analyses. Because there are some additions and deletions of product modules over the years, we only keep purchases in the product modules that exist for all years in the data.

Nielsen Consumer Panel Data contains demographic information for *both* wives and husbands for married-couple households. Age, education, hours employed[10], and occupation[11] are recorded for both household heads and the spouses. The availability of these information at the individual level allows us to control for spouse-level characteristics in our analyses. Other demographic characteristics, such as race, family size, number of children, place of residence, and household

[8]Note that the coverage of “Fresh Produce" is limited because it is only recorded for the items with barcodes. Other products that does not have barcodes, such as random weighted fruit, vegetables, and in-store baked-goods are not recorded by all Nielsen households.

[9]Hence, it should be noted that this dataset does not capture full household consumption. This data represents household consumption on frequently purchased, grocery-related items that are brought to home.

[10]Work hours, conditional on working, are reported in three broad categories: (1) Under 30 hours, (2) 30-34 hours, and (3) 35+ hours.

[11]There are 12 categories for occupation variable that is recorded for household heads and spouses.

income[12], are reported at the household level.

3.3.2 Industry Share and Wage

For constructing a Bartik-style measure of potential relative wages, we use two data sources, (i) US 5% population census (2000), which is used to construct industry shares, and (ii) Quarterly Census of Employment and Wages (QCEW) 2004-2017, which is used to construct wages.[13] QCEW reports quarterly employment and wages reported by employers, covering more than 95% of US jobs. The data is available by industry at the county levels. We use annual version of QCEW data for constructing annual wage levels. Specifically, we obtain γ_{grecj}, the proportion of female (male) workers of race r and education e in industry j in county c from the 2000 Census and w_{-cyj}, statewide annual wages in industry j calculated from the counties except for the focal county c in year y, from the QCEW.

3.4 Descriptive Statistics

3.4.1 Gender Differences in Consumption: Singles Living Alone

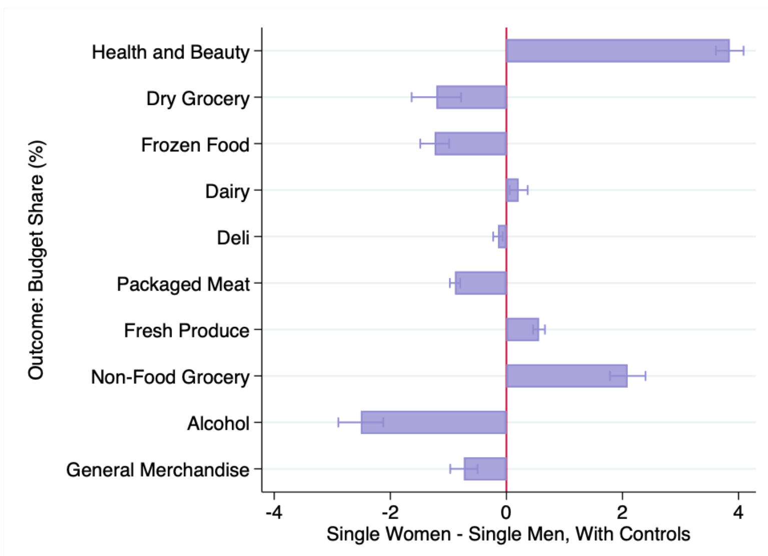
In order to understand consumption patterns of married couples, it is crucial for us to examine whether there are gender differences in consumption preferences. Because Nielsen consumer data only records consumption at the household-level, not at the individual-level, it is challenging to measure the individual consumption of each spouse. For example, we may observe that the household purchased some apples, but we do not observe who bought and consumed them. For gender-assignable goods, we can still infer preferences from observing household level expenditures (Dunbar, Lewbel, and Pendakur, 2013; Ahn, 2022; Calvi, 2020). However, given that Nielsen mainly records grocery-related items, we need to find another way to understand each gender's preferences.

[12] Household incomes are reported as bins with 20 categories and with a two-yer lag.

[13] We follow 2-digit NAICS industry classifications.

To understand differential preferences of men and women, we document consumption patterns of single men and single women who are living alone. The purpose of these exercises is to understand if certain aggregate goods are preferred largely by a particular gender. Using singles sample, we regress expenditure share on each aggregate good on a female indicator, while controlling for various individual-level characteristics including age, years of education, unemployment status, household income, races, as well as year and county fixed effects. We show the results in Figure 3.1. We find that women tend to spend more on health and beauty, dairy, fresh produce, and non-food grocery, even after controlling for individual observable characteristics and various fixed effects. On the other hand, we find that men have a tendency to spend more on dry food, frozen food, packaged meat, alcohol and general merchandise.

Figure 3.1: Consumption Patterns by Single Women vs Single Men Living Alone, by Department



Note: Consumer Panel 2004-2017. Sample only includes singles living alone who are between age 25-64. This figure shows the result from regression of budget share for corresponding aggregate good (y-axis) on female indicator and various controls. The bar indicates the regression coefficient on the female indicator. Control variables included in the regressions are: age, years of education, unemployment status, household income, dummies for Black and Hispanic, year fixed effects, county fixed effects. Household weights are applied. Standard errors are clustered at the county level.

Raw mean budget shares for each gender are presented in Figure C.1, which supports that the largest gender differences in budget shares are from health and beauty aids and alcohol. Although raw mean budget shares show some degree of gender differences in all of the aggregate goods, the largest gender gaps relative to the base mean budget shares are shown in health and beauty aids and alcohol categories. For example, Figure C.1 shows that single men, on average, allocate twice larger budget shares on alcohol than single women do. In order to further explore if there exist gender differences among finer categories of alcohol, we divide the alcohol consumption into beer, liquor, and wine, using the product group categorization provided by Nielsen. Figure C.3 shows the gender differences in detailed alcohol categories: This shows that the gender differences is largest in the beer consumption, whereas there is no statistically significant gender difference in the wine consumption, after controlling for the individual characteristics and year and county fixed effects.

In summary, although it is difficult to identify a perfect women-exclusive good or men-exclusive good on which the opposite gender spends zero amount among the aggregate goods at the department level, health and beauty for women and alcohol for men appear to be two categories whose consumption is more concentrated on a single gender. Among alcohol categories, beer appears to be an aggregate good that is particularly preferred by men more than by women. This pattern of consumption is consistent with the findings in the previous literature where increases in wife's power are associated with decreases in alcohol expenditures (Phipps and Burton, 1998; Hoddinott and Haddad, 1995; Attanasio and Lechene, 2014; Ward-Batts, 2008) and increases in spending on cosmetic goods (Ahn, 2022). For food consumption, women appear to have a stronger preference on healthier diets, spending more on fresh produce and dairy and less on frozen food and packaged meat.

3.4.2 Married Couple Sample

In this section, we describe the sample of married couples that we use in our main analyses. Because we study the effects of gender-relative labor market condition on consumption of married couples, we limit our sample to married couples where both husbands and wives are working ages, which we define to be between age 25-64. Table 3.1 shows the summary statistics of annual total expenditure of married couples in our sample. As shown in the first row of the table, untrimmed total expenditure has an outlier problem: Minimum annual total expenditure is shown to be $1.7 and the maximum value is $34,684.4. To alleviate this issue, we drop the couples with annual total expenditure value below the 1st percentile and above the 99th percentile from our sample. Second row of Table 3.1 shows the summary statistics of trimmed sample based on total expenditure. The mean annual expenditure of Nielsen-tracked items is $4,175.8 and the median is $3,876.4 for our married couple sample.

Table 3.1: Statistics on Total Annual Expenditure, Married Couples

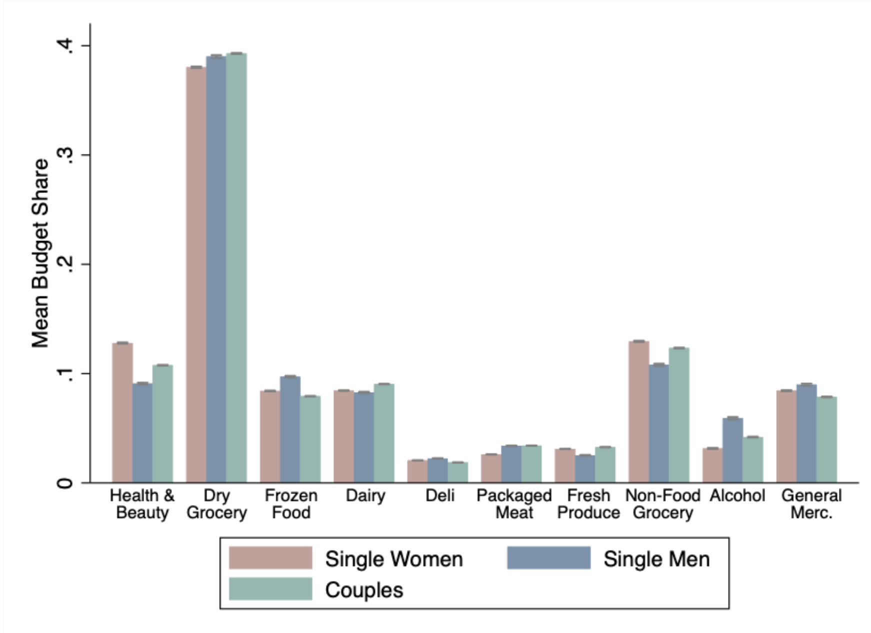
	# of Obs	Mean	Min	p1	p25	p50	p75	p99	Max
Toal Expenditure (Untrimmed)	340738	4223.2	1.7	949.8	2712.3	3876.4	5326.3	10711.2	34684.4
Toal Expenditure (Trimmed)	333924	4175.8	949.8	1195.5	2736.0	3876.4	5289.5	9615.9	10711.2

Note: Nielsen Consumer Panel 2004-2017. Sample is limited to couples whose both husband and wive are age 25-64. Dollars are inflation-adjusted and based on 2010 dollars.

Appendix Table C.2 shows summary statistics of our married couple sample from the Nielsen Consumer Panel. Average household income is approximately $69,633 in 2010 USD among the households in our sample. Average age of our sample is 49.7 for husbands and 48.0 for wives. Years of education are 14.38 and 14.58 for husbands and wives, respectively. Household size is on average 3.13, suggesting that the sample includes households with children. Unemployment of wives is twice higher than of husbands.

Figure 3.2 compares the mean budget share of married couples with single women and men. For more straightforward comparison between couples and singles, we only include couples without children and singles living alone in this figure. On average, married couples allocates more budget share on dry grocery, dairy, packaged meat, and fresh produce than singles do. Moreover, on average, married couples allocates less budget share on frozen food, deli, and general merchandise than singles do. On certain aggregate goods including health and beauty aids, alcohol, and non-food groceries, married couples' budget shares are in between single women's and single men's budget shares.

Figure 3.2: Mean Budget Shares by Gender, Singles and Couples Without Child



Note: Nielsen Consumer panel 2004-2017. Sample is limited to single men and women living alone and couples without child. Sample only includes those aged 25-64. This plot shows the mean budget share for each consumption categories. 95% confidence intervals are indicated by the error bars.

To disentangle the effects of marital status from effects of other household characteristics, we regress each expenditure share on each aggregate good on a married couple indicator, while controlling for various household-level characteristics including head's age, head's years of education, head's unemployment status, household income, race, as well as year and county fixed effects. Appendix Figures C.2a and C.2b show the regression coefficients on married couple indicator using different subsamples. When compared to single women, married couples allocate significantly lower budget shares on health and beauty aids, non-food grocery, and general merchandise, and significantly higher budget shares on dry grocery, dairy packaged meat and alcohol. When compared to single men, married couples allocate significantly higher budget shares on health and beauty aids, dry grocery, dairy, fresh produce, non-food grocery, and significantly lower budget shares on frozen food, deli, alcohol, and general merchandise.

Figures C.2a and C.2b show that the aggregate goods in which the coefficients of married couples move in the opposite directions when compared to single women and to single men are: health and beauty aids, non-food grocery, and alcohol.

3.5 Spouse Relative Education and Married Couple's Consumption

In this section, we examine the effects of spouse relative education on consumption of married couples. Figure C.5 presents the distribution of differences of wife's and husband's years of educations in our married couple sample. It shows that around 40 percents of couples have same levels of education, and more than quarter of couples have wive more educated than the husbands. Using our married couple sample, we regress each expenditure share of each aggregate good on spouse relative education, defined by differences in years of education between wife and husband, while controlling for husband's years of education and also for various other household-level characteristics[14] and year and county fixed effects.

Figure 3.3 presents the regression coefficients on education difference between wife and husband.[15] Results show that higher relative wife's education, controlling for husband's education level, is associated with significantly higher budget shares on health care, on beauty products, on non-food grocery, and and on books, stationary, and school supplies. Higher relative wife's education is also associated with significantly lower budget share on alcohol and on tobacco and tobacco-related accessories. For most of these results, the relative education results seem consistent with the bargaining power story; for instance, beauty goods are more associated with female and alcohol is more associated with male, according to our descriptive statistics on single males and females in Section 3.4.1.

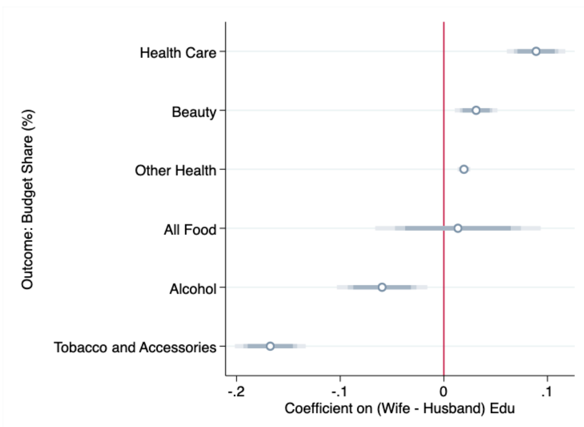
While the results exhibit interesting patterns, we need to be cautious with interpretations of our relative education results on consumption. A potential concern is that spouse relative education

[14]These other control variables include: household total expenditure, black, hispanic, household size, number of children, ages of female and male heads, and occupation fixed effects for male and female heads, which include unemployment as an omitted category.

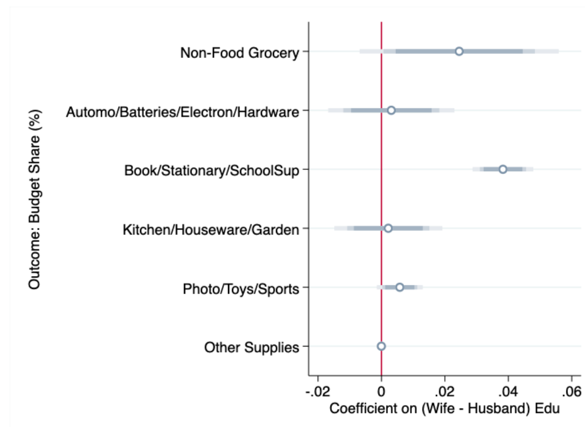
[15]Table versions of these regression results are presented in Appendix Table C.4 and C.6. We also show results using the same control set but without controlling for husband's education in Appendix Tables C.5 and C.7. We find similar results on beauty and alcohol budget shares even if we do not control for husband's education.

may not be exogenous, because couples do not match randomly based on education. Couples who match assortatively based on education may have different consumption preferences than couples who do not match with similarly educated partners. In order to address this potential endogeneity concern, we construct a spouse relative potential wage, which is a plausibly more exogenous measure of spouse bargaining power. This is discussed in the next section.

Figure 3.3: Effects of (Wife - Husband) Education on Household Budget Share



(a) Aggregate Good I



(b) Aggregate Good II

Note: This figure presents coefficient on (wife-husband) education. Sample is married couples whose both husband and wife aged 25-64 in 2004-2017 Nielsen Consumer Panel. Omitted control variables from the figure include: years of education of male head, household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, occupation fixed effects for male and female heads, county fixed effects, year fixed effects. Household weights are applied. The empty circle represents the value of corresponding regression coefficient, and the associated horizontal bars represent statistical significance level at 1% (lightest color), 5% (medium color), and 10% (darkest color) respectively. Standard errors are clustered at the county level.

3.6 Spouse Relative Potential Wage and Married Couple's Consumption

3.6.1 Construction of Gender Relative Potential Wage

To address potential endogeneity problems of using household level relative education, we construct a potential market (county) level relative wage using a Bartik-style approach, exploiting historical sex and race segregation by industry (Bartik, 1991; Blanchard et al., 1992; Aizer, 2010;

Bertrand, Kamenica, and Pan, 2015; Shenhav, 2021).[16] Specifically, average annual wages are calculated by gender and race in each county as follows:

$$\bar{w}_{grecy} = \sum_j \gamma_{grecj} w_{-cyj} \tag{3.1}$$

where g, r, e, c, y, and j indicate gender, race, education (less than college or college+), county, year and industry, respectively. γ_{grecj} is the proportion of female (or male) workers of a given race and education working in industry j in county c and fixed over time to account for sorting through wages. To capture labor demand shocks uncorrelated with county specific characteristics, we construct w_{-cyj} as yearly state annual wage in industry j except for county c.

Taking out the focal county from the state annual wage is important to rule out the cases where characteristics of men and women in a particular market are affected by consumption, which is our outcome variable. For example, households in county c that consume more alcohol may be less productive, which may affect wage in county c. Our measure of average annual wages in county c removes this type of possibilities by taking the state-average wage except for county c.

With the constructed Bartik-style wage, the identification comes from the fact that the counties with higher shares in industry j which experiences large statewide wage growth will have larger increases in average wages than counties more concentrated with low-wage growth industries.

Our measure of gender wage ratio is the ratio of female to male wages constructed according to the above formula. We match the constructed gender wage ratio with the household consumption data based on gender, race, and education of each spouse annually for each county. Mean spouse wage ratio is 0.94 and the standard deviation is 0.09 in our married couple sample. 25th percentile is 0.90 and 75th percentile is 0.97.

[16] Table C.3 shows different industry distributions for men and women.

3.6.2 Empirical Specification

To estimate the impact of the gender wage gap on household consumption for the married couples, we use the gender wage ratio that is constructed for each couple using Bartik measure for female and male potential wages as described in Section 3.6.1. Specifically, we first match the Bartik gender wage to each spouse in our married couple sample by year, race, education, and county. Then, the resulting gender wage ratio for each household becomes:

$$GenderWageRatio_{re_he_wcy} = \frac{\bar{w}_{female,re_wcy}}{\bar{w}_{male,re_hcy}}$$

where h indexes household, c county, y year, r race, e_h husband's education, and e_w wife's education.

The following model is estimated using the matched consumption and wage data for the period 2004 to 2017:

$$BudgetShare_{hcy} = \alpha + \beta GenderWageRatio_{re_he_wcy} + \gamma \mathbf{X}_{hy} + \theta_c + \pi_y + \varepsilon_{hyd} \qquad (3.2)$$

where budget share is defined as expenditure on certain aggregate good divided by total expenditure for each household in each year. The household-level control set $\mathbf{X}$ includes: household total expenditure,[17] Black, Hispanic, household size, number of children in the household, ages of male and female heads, occupation dummies of female and male heads, years of education for male and female heads. Year fixed effects and and county fixed effects are included. Therefore, we exploit variations in gender wage gap within counties over time after accounting for year effects common to all counties. We use the constructed gender wage ratio in the reduced from rather than using it as an instrumental variable, allowing for different mechanisms through which the wage gap affects consumption patterns.

[17] Controlling for total expenditure, instead of household income, is a common practice in the budget share regressions. However, we also estimate Equation (2) using household income as a control variable instead and find very similar results. These results are available upon request.

In order to further understand the respective effect of each gender potential wage, we also estimate the above regression using constructed male and female potential wages together as variables of interest instead of gender wage ratio. The second equation to be estimated is:

$$BudgetShare_{hcy} = \alpha + \beta_m MaleWage_{re_h cy} + \beta_f FemaleWage_{re_w cy} + \gamma \mathbf{X}_{hy} + \theta_c + \pi_y + \varepsilon_{hyd} \tag{3.3}$$

This would allow us to see the effects of an increase in husband's potential wage while fixing wife's potential wage on household consumption, and vice versa.

3.7 The Impacts of Relative Wage on Household Consumption

3.7.1 Aggregate Goods I: Health and Beauty, Food, Alcohol, Tobacco

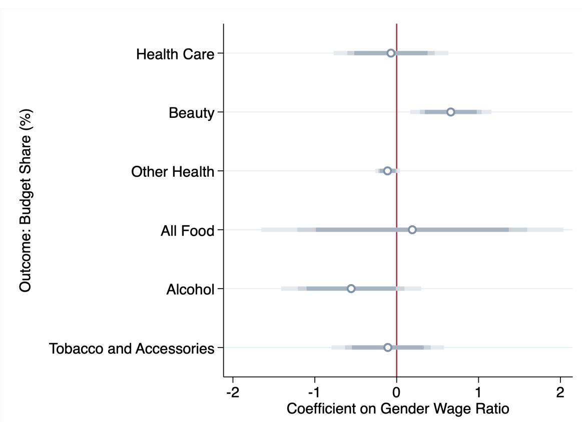
In this section, we present the estimation results from regressing Equation 3.2. Figure 3.4a reports the regression coefficient on female-to-male wage ratio for the following Nielsen departments: health and beauty aids, food, alcohol, and tobacco and accessories.[18] Full regression results and raw mean of each budget share are reported in Appendix Table C.9. The results shows that an increase in the female-to-male wage ratio is associated with an increase in budget share for beauty and a decrease in budget share for alcohol, both of which are statistically significant at the 1% level. The magnitude of these effects is considerable: considering that one standard deviation of gender wage ratio is 0.085 in our data, budget share on beauty (mean budget share: 3.5%) increases by 0.057 percentage point and budget share on alcohol (mean budget share: 2.8%) decreases by 0.051 percentage point as the wage ratio increases by one standard deviation. There is a less statistically significant effect on "Other Health" category, which mostly includes men's toiletries. The effects of gender wage ratio on other consumption categories are insignificant.

To further understand the finding, we estimate Equation 3.2 on the same set of outcomes using

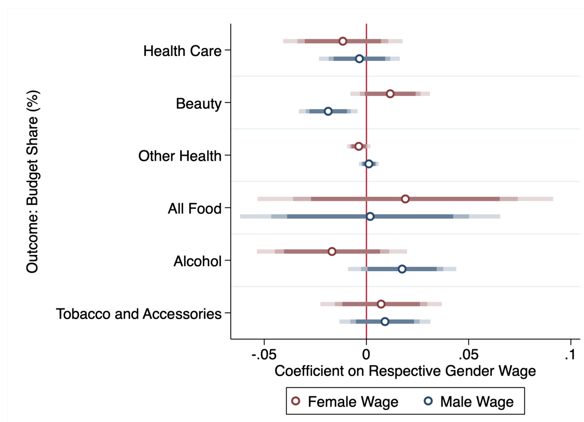
[18]We divide "Health and Beauty Aids" department into three sub-categories using product group categorization. Specifically, "Health Care" includes cough and cold remedies, diet aids, first aid, sanitary products, vitamins. "Beauty" includes cosmetics, fragrances for women, hair care, skin care preparation, shaving needs. "Other Health" includes men's toiletries and baby needs.

respective gender wages instead of female-to-male wage ratio. Figure 3.4b presents the coefficients on female and male potential wages. Table version of these results is reported in Appendix Table C.9. The result shows that female wage and male wage have opposite effect on beauty budget share. Fixing the male wage, an increase in female wage significantly increases beauty budget share of the households. Fixing the female wage, an increase in male wage significantly decrease beauty budget share, both statistically significant at the 5% level. Moreover, male and female wages have opposite effects on the budget share for alcohol; an increase in male wage increases alcohol budget share, which is statistically significant at 5% level, while an increase in female wage is associated with a decreasing effect on alcohol, although the effect on female wage is not statistically significant. The result also shows that an increase in female wage has a statistically significant decreasing effect on “Other Health" budget share.

Figure 3.4: Results on Overall Consumption Budget Share, Aggregate I



(a) Female-to-Male Wage Ratio



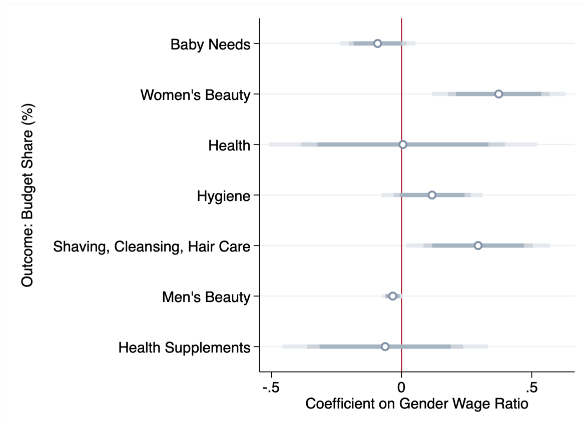
(b) Respective Gender Wages

Note: This figure presents coefficient on gender wage ratio in Panel (a) and coefficients on female and male wages in Panel (b) from the corresponding regressions using Equation 3.2. Sample is married couples with both wife and husband aged 25-64 in 2004-2017 Nielsen Consumer Panel. Omitted control variables from the figure include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, years of education of female and male heads, occupation fixed effects for male and female heads, county fixed effects, year fixed effects. Household weights are applied. The empty circle represents the value of corresponding regression coefficient, and the associated horizontal bars represent statistical significance level at 1% (lightest color), 5% (medium color), and 10% (darkest color) respectively. Standard errors are clustered at the county level.

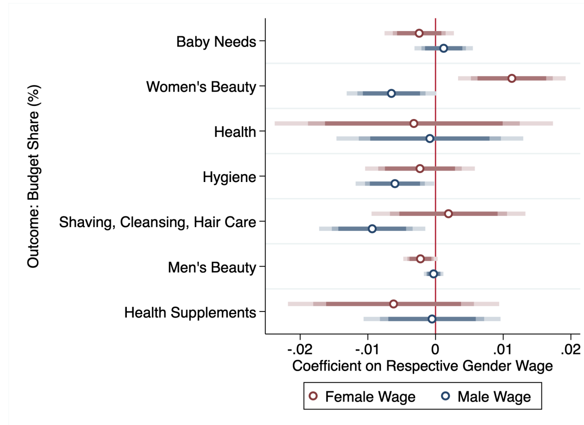
Recall that the evidence from Section 3.4, which compares consumption pattern of single men and women, suggests beauty is more likely to be female good and alcohol is more likely to be male good. Our results on married couple households suggest that an increase in female-to-male wage ratio affects household budget share in a way that is more favorable to wives through increasing budget share for beauty and decreasing budget share for alcohol.

To better understand the above results, we further categorize aggregate goods into finer categories using the product module definition given by Nielsen. These more detailed aggregate goods better reflect the gender association of each aggregate good. For example, some product modules explicitly document their gender association, such as “Women’s gift sets & skin care packages" and “Women’s hair spray." Along with these explicitly documented gender goods, we categorize other cosmetics-related product modules that are largely used by women, such as lipsticks and nail polish, as “Women’s Beauty" goods. In Figure 3.5, we present results for more detailed categories of health and beauty aids. Table versions of the results and mean budget shares are reported in Appendix Tables C.14 and C.15. Figure 3.5a shows that higher female-to-male wage ratio significantly increases household budget shares on women’s beauty items and shaving, cleansing, and hair care items. This result confirms that the positive effect on beauty good that we see in Figure 3.4a is indeed driven by items more associated with women. Figure 3.5b shows that for women’s beauty goods and shaving, cleansing, and hair care, the effects of female potential wage and male potential wage move in the opposite direction.

Figure 3.5: Results on Overall Consumption Budget Share, Detailed Health and Beauty Aids



(a) Female-to-Male Wage Ratio

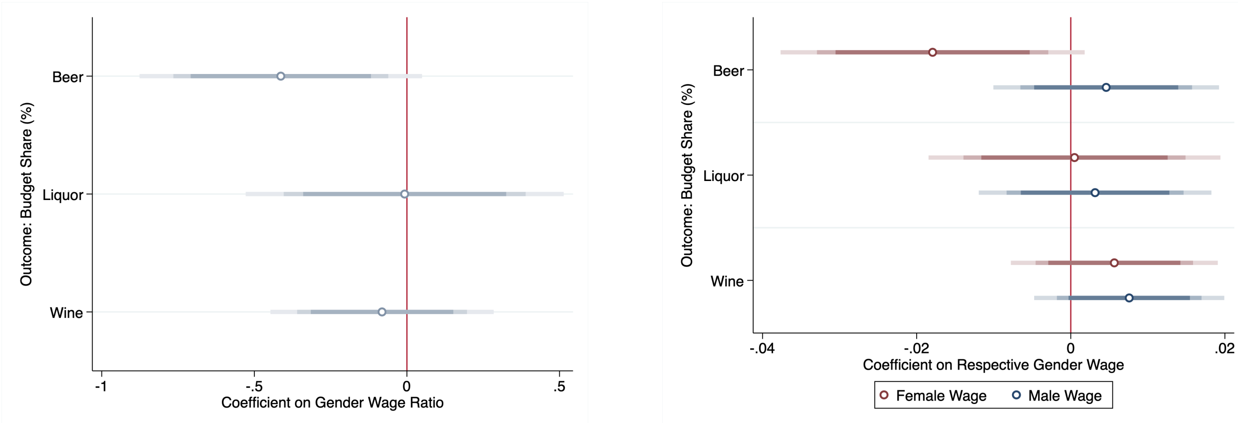


(b) Respective Gender Wages

Note: This figure presents coefficient on gender wage ratio in Panel (a) and coefficients on female and male wages in Panel (b) from the corresponding regressions using Equation 3.2. Sample is married couples with both wife and husband aged 25-64 in 2004-2017 Nielsen Consumer Panel. Omitted control variables from the figure include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, years of education of female and male heads,o ccupation fixed effects for male and female heads, county fixed effects, year fixed effects. Household weights are applied. The empty circle represents the value of corresponding regression coefficient, and the associated horizontal bars represent statistical significance level at 1% (lightest color), 5% (medium color), and 10% (darkest color) respectively. Standard errors are clustered at the county level.

We also present results for detailed categories of alcohol. Figure 3.6a shows that higher female-to-male wage ratio decreases the household budget share on beer, and this effect is statistically significant at 5% level. We do not see statistically significant effect on liquor and on wine. This result is interesting as beer is a good that single men seems to prefer more than single women do (Figure C.3). Figure 3.6b shows that fixing male potential wage, increase in female potential wage decreases the household budget share on beer, and this effect is statistically significant at 5% level. Another interesting pattern is that, although statistically insignificant, coefficients on male wage are all positive, while coefficient on female wage is only positive for wine, which is a good that we do not see gender differences when using single sample (Figure C.3).

Figure 3.6: Results on Overall Consumption Budget Share, Detailed Alcohol



(a) Female-to-Male Wage Ratio

(b) Respective Gender Wages

Note: This figure presents coefficient on gender wage ratio in Panel (a) and coefficients on female and male wages in Panel (b) from the corresponding regressions using Equation 3.2. Sample is married couples with both wife and husband aged 25-64 in 2004-2017 Nielsen Consumer Panel. Omitted control variables from the figure include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, years of education of female and male heads,o ccupation fixed effects for male and female heads, county fixed effects, year fixed effects. Household weights are applied. The empty circle represents the value of corresponding regression coefficient, and the associated horizontal bars represent statistical significance level at 1% (lightest color), 5% (medium color), and 10% (darkest color) respectively. Standard errors are clustered at the county level.

Overall, our results on all consumption categories support that higher relative female wage is associated with higher budget share for consumption categories that are likely to be more preferred by wives.

3.7.2 Aggregate Goods II: Non-Food Grocery and General Merchandise

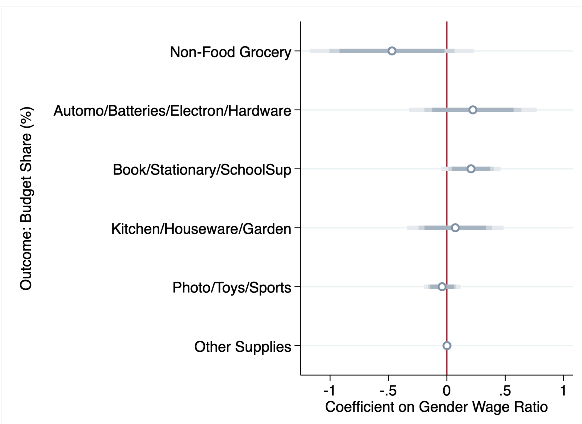
We now present the estimation results for the remaining consumption categories, which are non-food grocery and general merchandise.[19] Figure 3.7a and Appendix Table C.10 show the estimation results using the female-to-male wage ratio as a main explanatory variable. The only statistically significant effect of gender wage ratio is shown for the budget share for “Books, Sta-

[19]We divide “General Merchandise" into several subcategories, which are (1) Automotive, Batteries, Electronic, Hardware, (2) Books, Stationary, School Supplies, (3) Kitchen, Houseware, Garden Supplies, (4) Photographic, Toys, Sporting goods, and (5) Other Supplies.

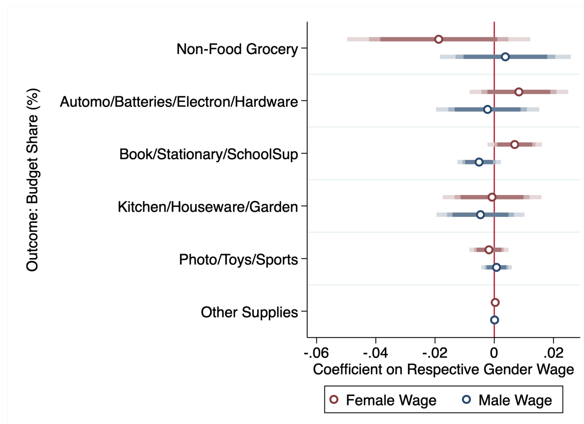
tionary, and School Supplies."

Figure 3.7b and Appendix Table C.11 shows the estimation results for the same outcomes with respective gender wages as main variables of interest instead of gender wage ratio. Result shows that an increase in female wage has statistically significant decreasing effect on the budget share for non-food grocery, which includes household cleaning supplies, laundry supplies, detergents, etc. An increase in male wage significantly decreases the budget share for books, stationery, and school supply.

Figure 3.7: Results on Overall Consumption Budget Share, Aggregate II



(a) Female-to-Male Wage Ratio

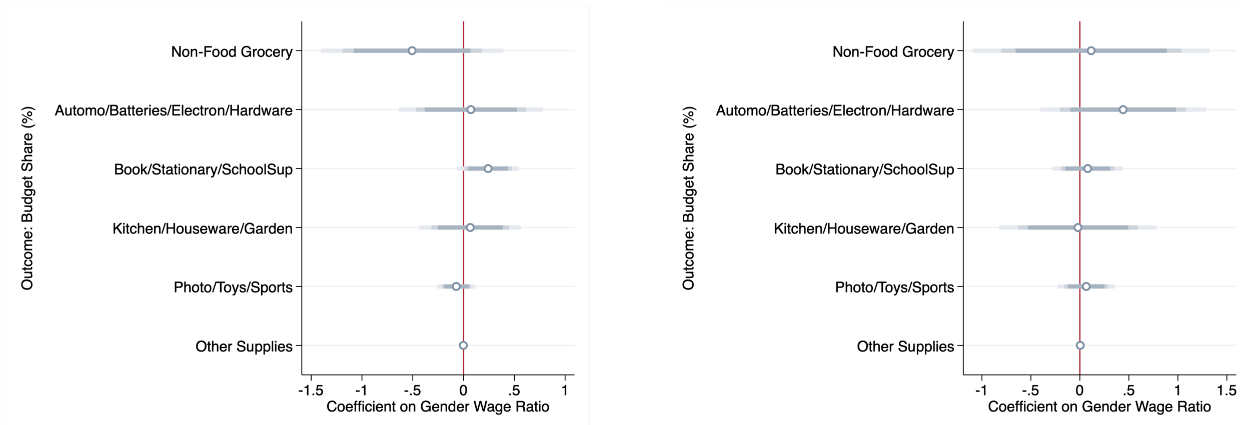


(b) Respective Gender Wages

Note: This figure presents coefficient on gender wage ratio in Panel (a) and coefficients on female and male wages in Panel (b) from the corresponding regressions using Equation 3.2. Sample is married couples with both wife and husband aged 25-64 in 2004-2017 Nielsen Consumer Panel. Omitted control variables from the figure include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, years of education of female and male heads, occupation fixed effects for male and female heads, county fixed effects, year fixed effects. Household weights are applied. The empty circle represents the value of corresponding regression coefficient, and the associated horizontal bars represent statistical significance level at 1% (lightest color), 5% (medium color), and 10% (darkest color) respectively. Standard errors are clustered at the county level.

In order to further investigate whether the positive effect of gender wage ratio on “Books, Stationary, and School Supplies" are related to child investment, we divide the sample into couples with child(ren) and couples without any child. Figure 3.8a shows the effect of gender wage ratio for couples with child(ren), and Figure 3.8b shows the effect for couples without child. We see that the significantly positive effect on “Books, Stationary, and School Supplies" only exist for couples *with* child(ren). This result may be consistent with previous literature that find a higher bargaining power of wives lead to greater spending on children (Lundberg, Pollak, and Wales, 1997; Duflo, 2003). We plan to further investigate the items in this category to see if this result indeed reflects the investment in children.

Figure 3.8: Results on Overall Consumption Budget Share, Aggregate II, By Child Status



(a) Couples with Child(ren)

(b) Couples without Child

Note: This figure presents coefficient on gender wage ratio using different subsamples by child status from the regression using Equation 3.2. Sample is married couples with both wife and husband aged 25-64 in 2004-2017 Nielsen Consumer Panel. Omitted control variables from the figure include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, years of education of female and male heads, occupation fixed effects for male and female heads, county fixed effects, year fixed effects. Household weights are applied. The empty circle represents the value of corresponding regression coefficient, and the associated horizontal bars represent statistical significance level at 1% (lightest color), 5% (medium color), and 10% (darkest color) respectively. Standard errors are clustered at the county level.

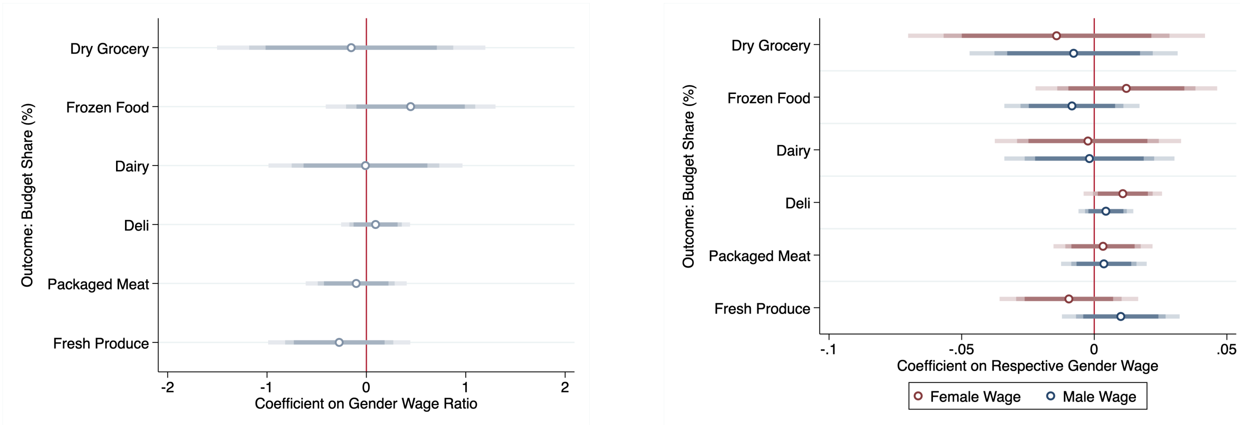
3.7.3 Food Consumption Categories

We now investigate results on food consumption. The results presented in this section is estimated from Equation 3.2 where each outcome variable is defined as food budget share for each food category. Food budget share is calculated by dividing the expenditure of each food categories by the total expenditure on food. Figure 3.9a and Appendix Table C.12 present the regression results where the female-to-male wage ratio is the variable of interest. We find that there are no statistically significant effects of gender wage ratio on each food budget share, although there is a limited evidence that frozen food budget share seems to increase.

Figure 3.9b and Appendix Table C.13 present the estimation results for food budget share with respective gender wages as main variables of interest. Coefficients on female and male wages are not statistically significant for most outcomes. An increase in female wage is associated with a significant decrease in budget share for dry grocery and a significant increase in budget share for deli. An increase in male wage is associated with a significant increase in fresh produce budget share. However, as discussed in Section 3.3, fresh produce is imprecisely measured in our sample.

Because each food category may contain products of heterogeneous nutritional quality, it is difficult to interpret our current findings on food consumption in terms of healthy diet. In our future analyses, we plan to look at finer categories of food consumption to better understand the role of relative potential wage on household nutritional outcomes.

Figure 3.9: Results on Food Budget Share



(a) Female-to-Male Wage Ratio

(b) Respective Gender Wages

Note: This figure presents coefficient on gender wage ratio in Panel (a) and coefficients on female and male wages in Panel (b) from the corresponding regressions using Equation 3.2. Sample is married couples with both wife and husband aged 25-64 in 2004-2017 Nielsen Consumer Panel. Omitted control variables from the figure include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, years of education of female and male heads,occupation fixed effects for male and female heads, county fixed effects, year fixed effects. Household weights are applied. The empty circle represents the value of corresponding regression coefficient, and the associated horizontal bars represent statistical significance level at 1% (lightest color), 5% (medium color), and 10% (darkest color) respectively. Standard errors are clustered at the county level.

3.8 Robustness

3.8.1 Alternative Channels

Our results for married-couple households show that an increase in female to male wage ratio affects household consumption on non-food categories in a way that is more favorable to wives. A prominent mechanism explaining these results is a higher bargaining power of wives within the households. However, there could be other potential channels at work. For instance, changes in total family income level induced by changes in gender wage ratio may lead to different consumption patterns. Another possible channel driving our results on household budget shares is the changes in labor supplies of men and women that are induced by the changes in gender wage ratio.

We test the income channel by examining the impacts of gender wage ratio on total income or expenditure of households. Because household income in Nielsen Consumer Panel is reported with a two-year lag, we test the income channel using both contemporaneous income and the originally reported income in the two-year lag. Table 3.2 presents the regression result with household contemporaneous income (Column (1)), originally reported household income with a two-year lag (Column (2)), and total household expenditure (Column (3)) as outcome variables. The result shows that the gender wage ratio does not have a statistically significant effect on either household income or total expenditure of married couples. This finding rejects the explanation that our main results in Section 3.7 are driven by the increase in household income or expenditure.

We currently have not examined whether the labor supply channel explains our results. It is possible that the higher female-to-male potential wage ratio has induced wives to work more. This may increase the beauty consumption if make-ups are valuable inputs for work. However, the labor supply channel does not explain why the female and male potential wage have opposite effects on alcohol budget share. In our future analyses, we plan to examine the link between gender wage ratio, changes in labor supplies, and household consumption using data containing labor supplies of husbands and wives (e.g. ACS, PSID).

Table 3.2: Effect of Gender Wage Ratio on Household Outcomes

	(1) Income (1,000 USD) b/se	(2) Income (1,000 USD), 2 Year Lag b/se	(3) Total Expenditure (1,000 USD) b/se
(Female Wage)/(Male Wage)	-0.6063	-0.5106	0.0021
	(2.5589)	(1.9331)	(0.1310)
Observations	196008	339189	339187
Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R-squared	0.428	0.442	0.121

Note: 2004-2017 Consumer Panel. Sample is married couples with both wife and husband aged 25-64 in 2004-2017 Nielsen Consumer Panel. All dollars are inflation-adjusted and in 2010 dollars. Omitted control variables from the table include: all the demographic controls, county fixed effects, year fixed effects. Household weights are applied. Standard errors are clustered at the county level.

3.8.2 Placebo Checks Using Singles Living Alone

In order for the bargaining power channel for couples to be valid, we should not expect the opposite gender wage to affect the expenditure share of singles living alone, because they do not have someone else in the household to bargain with. As a placebo test, we examine if relative gender wage affect consumption of single individuals living alone. In this exercise, we limit our sample to age age 25-64 singles who are living alone. We match the singles sample to the Bartik wage data for their own gender based on year, county, education level, and race. We also match the opposite gender wage for same year, county, education level, and race to the singles sample. Using the matched data, we estimate the Equation 3.3 for single men and women, respectively. The results are presented in Table 3.3.

The results show that the opposite gender wage do not have a statistically significant effect on any of the consumption outcomes for single sample. Table 3.3 shows that although female's potential wage has a statistically significant positive effects on single female's beauty consumption, male's potential wage does not have significant effect on any of the female consumption. Similarly, it also shows that although the increase in male potential wage has a positive effect on single male's alcohol consumption – significant at the 10% level, female potential wage does not have any statistically meaningful effect on single male's consumption. In Appendix Table C.16, we show that the gender wage ratio also does not have any significant effect on single's consumption. We view these results as further confirming that the relative gender wage only influences married couple's consumption.

Table 3.3: Effect of Respective Gender Wage on Budget Share (%), Singles Living Alone

	(1) Health Care	(2) Beauty	(3) Other Health	(4) All Food	(5) Alcohol	(6) Tobacco and Accessories
Panel A: Single Female Living Alone						
Female Wage (1,000 USD)	0.007	0.053*	-0.000	-0.035	-0.020	0.012
	(0.053)	(0.032)	(0.004)	(0.104)	(0.039)	(0.058)
Male Wage (1,000 USD)	-0.020	-0.055*	0.002	-0.024	0.018	0.065
	(0.050)	(0.028)	(0.002)	(0.091)	(0.031)	(0.044)
Budget Share Mean (%)	8.302	4.342	0.170	62.550	3.159	2.541
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82267	82267	82267	82267	82267	82267
Panel B: Single Male Living Alone						
Female Wage (1,000 USD)	0.031	0.003	0.001	-0.061	-0.089	0.085
	(0.061)	(0.036)	(0.005)	(0.198)	(0.099)	(0.110)
Male Wage (1,000 USD)	-0.001	-0.000	-0.002	0.109	0.107	0.005
	(0.051)	(0.045)	(0.003)	(0.174)	(0.087)	(0.081)
Budget Share Mean (%)	6.845	2.109	0.163	65.091	5.938	3.209
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41401	41401	41401	41401	41401	41401

Note: 2004-2017 Consumer Panel. In Panel A, the sample is limited to single females aged 25-64 living alone. In Panel B, the sample is limited to single males aged 25-64 living alone. Control variables include: total expenditure, dummies for Black, Hispanic, age, years of education, occupation categories. County fixed effects and year fixed effects are included. Household weights are applied. Standard errors are clustered at the county level. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

3.8.3 Rotemberg Weight

We conduct the robustness check proposed by Goldsmith-Pinkham, Sorkin, and Swift (2020) to document the variation that drives our Bartik estimates for each gender's potential wage. Rotemberg weight measures the relative importance of each industry share in determining parameter estimates. These weights are calculated by decomposing the Bartik estimator into a weighted combination of just-identified estimates based on each industry share. Because our measure of female-to-male potential wage ratio is constructed in a way that cannot be decomposed into a combination of industries, we instead decompose the estimators for female potential wage and male potential wage, respectively. Specifically, we examine which industries contribute most to parameter estimates for β_m and β_f, respectively, when estimating Equation 3.3. For the calculation of Rotemberg weights for each gender wage, we select two outcomes that show highly statistically significant coefficient on each gender wage in Section 3.7. Outcomes selected for female potential wage are: household budget shares on women's beauty items and on beer. Outcomes selected for male potential wage are: household budget shares on women's beauty items and on alcohol. We describe the detailed estimation procedure for the Rotemberg weights in Appendix C.3.

Rotemberg weights are reported in Appendix Table C.17 for female potential wage and Appendix Table C.18 for male potential wage. In Part I of each panel, we show the proportion of positive and negative Rotemberg weights for each industry. Both tables show that the share of negative weights are very small, which means our Bartik estimates do have a LATE-like interpretation as weighted averages of treatment effects as explained in Goldsmith-Pinkham, Sorkin, and Swift (2020). In Part II of each panel, we show top 5 industries for each gender potential wage. Note that the Rotemberg weights are not the function of outcome variables as outlined in Appendix C.3, and hence they are same across outcomes in each table. Although no single industry is contributing to the majority of the identifying variation for each gender's potential wage, top five Rotemberg industries account for a big proportion of the positive weight in the estimator, over 93% for female potential wage and 79% for male potential wage. However, we observe that point estimates across top five instruments are very similar and close to overall point estimates for the main outcomes, and this confirms that no single industry is driving the point estimate of our Bartik estimator.

3.9 Structural Estimation: The Impacts of Relative Wages on Couples' Sharing Rule

In previous sections, we showed how relative wages affect expenditures on different categories. In this section, we study how relative wages influence couples' sharing rule (i.e., how couples split resources within households). Specifically, we use a structural model with a collective model approach which allows us to recover how sharing rule responds to relative wages. The identification is based on the results from Chiappori, Fortin, and Lacroix (2002).

Model

We assume egoistic preferences where each agent cares only about his or her own consumption.[20] The utility function can be represented as $u^i(\mathbf{q}^i, \mathbf{s})$ where i denotes the agent (i.e., $i = h, w$). $\mathbf{q}^i$ and $\mathbf{s}$ indicate the consumption of agent i and preference factors such as age and education level, respectively. $\mathbf{q}^i$ can be either gender-exclusive goods or assignable goods from which we can observe individual consumption patterns. We assume a well-behaved utility function that is strictly quasi-concave, increasing, and continuously differentiable. We assume that the agents face the same prices.

The household solves the following program:

$$\max_{\mathbf{q}^h, \mathbf{q}^w} u^h(\mathbf{q}^h, \mathbf{s}) + \mu(\mathbf{s}, \mathbf{z}) u^w(\mathbf{q}^w, \mathbf{s}) \tag{3.4}$$

subject to

$$\mathbf{e} \cdot (\mathbf{q}^h + \mathbf{q}^w) \leq x$$

where $\mathbf{e}$, $\mathbf{s}$, $\mathbf{z}$, and x denote a price vector of ones, a vector of preference factors, a vector of distribution factors, and total expenditure, respectively. Pareto weight μ is a function of $\mathbf{s}$ and $\mathbf{z}$ and is assumed continuously differentiable with respect to each argument. Note that distribution factors, $\mathbf{z}$, affects consumption choice only through μ. In other words, when $\mathbf{z}$ changes, the allocation moves along the Pareto frontier without changing the Pareto frontier.

Under the egoistic preference assumption, the above problem is equivalent to solving two problems of husbands and wives. That is, there exist *sharing rule* functions $\phi^h(x, \mathbf{s}, \mathbf{z})$ and $\phi^w(x, \mathbf{s}, \mathbf{z})$ such that $\phi^h + \phi^w = x$. Each member solves the program below:

$$\max_{q^i} u(\mathbf{q}^i, \mathbf{z}) \tag{3.5}$$

[20]The model can be extended to have Beckerian “caring" preferences.

subject to

$$\mathbf{e} \cdot \mathbf{q}^i \leq \phi^i$$

where $i = h, w$. The result follows from the second fundamental theorem of welfare economics. Any Pareto efficient allocation can be achieved as a competitive equilibrium with a lump-sum wealth redistribution. For the complete proof, see Browning et al. (1994).

Assuming interior solutions, equation (3.5) yields demand equations for husbands and wives. we focus on two gender-exclusive goods, one for the husband and one for the wife. The demand functions are as follows:

$$c^h = C^h(\phi^h(x, \mathbf{s}, \mathbf{z}), \mathbf{s}) \tag{3.6}$$

$$c^w = C^w(x - \phi^h(x, \mathbf{s}, \mathbf{z}), \mathbf{s}) \tag{3.7}$$

where C^i is a demand function for member i ($i = h, w$). These two equations allow us to identify the partials of the sharing rule. The identification result closely follows Chiappori, Fortin, and Lacroix (2002). The idea is using the fact that total expenditure and distribution factors affect consumption behavior only through the sharing rule. The responses of the consumption behaviors to these variables allow us to estimate the marginal rate of substitution between x and $\mathbf{z}$ for husbands and wives.

To formalize this idea, let $A = \frac{\partial c^h/\partial z}{\partial c^h/\partial x}$ and $B = \frac{\partial c^w/\partial z}{\partial c^w/\partial x}$ when $\frac{\partial c^h}{\partial x} \cdot \frac{\partial c^w}{\partial x} \neq 0$. Assume that there is only one distribution factor. A and B are directly observable from the data. From the demand equations, $A = \frac{\partial c^h/\partial z}{\partial c^h/\partial x} = \frac{\phi^h_z}{\phi^h_x}$ and $B = \frac{\partial c^w/\partial z}{\partial c^w/\partial x} = \frac{-\phi^h_z}{1-\phi^h_x}$. Their relationships allow the recovery of the partials of sharing rule, ϕ^h_z and ϕ^h_x. They are given by the following:

$$\phi^h_x = \frac{B}{B - A} \tag{3.8}$$

$$\phi^h_z = \frac{AB}{B - A} \tag{3.9}$$

assuming that $A \neq B$.

Given the results above, the sharing rule can be identified up to a constant function $\kappa(\mathbf{z})$.

Estimation of the model

As two gender exclusive goods, we use women's and men's beauty goods.[21] We focus on married couples without children to make sure that the expenditures on gender-exclusive goods are solely for husbands and wives, not other members of the households. For the total expenditure, we use the total expenditure for Nielsen-tracked items. Therefore, we estimate how Nielsen-tracked expenditures are shared among couples, rather than how total household expenditures are shared. Note that the mean annual expenditure for Nielsen tracked items is $4,246.

We use an unrestricted linear functional form with one distribution factor given below:[22]

$$\text{Men's beauty}_{hy} = \alpha^h + \beta^h GenderWageRatio_{re_h e_w cy} + \tau^h x_{hy} + \gamma^h \mathbf{s}_{hy} + \theta_c^h + \pi_y^h + \varepsilon_{hy} \quad (3.10)$$

$$\text{Women's beauty}_{hy} = \alpha^w + \beta^w GenderWageRatio_{re_h e_w cy} + \tau^w x_{hy} + \gamma^w \mathbf{s}_{hy} + \theta_c^w + \pi_y^w + \varepsilon_{hy} \quad (3.11)$$

where $GenderWageRatio$ is our distribution factor z. x_{hy} is total expenditure and $\mathbf{s}_{hy}$ indicates preference factors including race dummies, household size, number of children in the household, ages of male and female heads, occupation dummies of female and male heads, years of education for male and female heads. θs and πs denote county fixed effects and year fixed effects, respectively. The dependent variables are defined as expenditure levels at the household for each gender-exclusive goods.

[21] Women's beauty goods and men's beauty goods are defined using relevant product modules, which are more detailed categories than product groups. Women's beauty goods include goods such as cosmetics, female fragrances, and female hair care. Men's beauty goods include items such as male hair care and men's toiletries.

[22] Any number of distribution factors can be incorporated.

The partials of sharing rule are given as follows:

$$\phi_x^h = \frac{\tau_2\delta_1}{\tau_2\delta_1 - \tau_1\delta_2} \tag{3.12}$$

$$\phi_z^h = \frac{\tau_1\delta_1}{\tau_2\delta_1 - \tau_1\delta_2} \tag{3.13}$$

Finally, the sharing rule equation is given by:

$$\phi^h = \frac{\tau_2\delta_1}{\tau_2\delta_1 - \tau_1\delta_2}x + \frac{\tau_1\delta_1}{\tau_2\delta_1 - \tau_1\delta_2}z + \kappa(\mathbf{z}) \tag{3.14}$$

$\kappa(\mathbf{z})$ is not identifiable, thus making the sharing rule identified up to a constant.

Sharing rule estimates

In this section, we present sharing rule estimates. The results are presented in Table 3.4. The partials of the sharing rule with respect to total expenditures and relative wages are both statistically significant. The partial with respect to the total expenditure is 0.52. This means that when total expenditure increases by one dollar, the shares of husbands increase by 0.52 unit. Naturally, wives take 0.48 unit. However, the difference between the shares of husbands and wives is not statistically significant, suggesting that additional dollars are shared equally between husbands and wives. The partial with respect to relative wages is estimated to be 749.6 dollars. This suggests that if relative wages increase by a standard deviation (0.085 in our data), the share of husbands decrease by 63.7 dollars, which correspond to 1.6% of the total expenditures counted in Nielsen. To understand the magnitude of the impact, we calculate income elasticities of demands for single men and women. Given the single men's income elasticity for alcohol demand, income reduction of 63.7 dollars leads to 4% decrease in alcohol expenditures. For women, income increase of 63.7 dollars results in 2.5% higher allocation on beauty goods. These estimates suggest that the changes in labor market meaningfully affect household allocations overall.

Table 3.4: Impacts of Gender Wage Ratio on Sharing Rule of Married Couples

	(1)
ϕ_x^h	.519***
	(.105)
ϕ_z^h	-749.586***
	(152.688)
Observations	140909

Notes: This table presents the estimates of the partials of the sharing rules with respect to total expenditures and a distribution factor. We use female-to-male wage ratio as our distribution factor. Included samples are households without children. Men's beauty goods and women's beauty goods are used as gender-exclusive goods. Control variables include: total expenditure, dummies for Black and Hispanic, age, years of education, occupation categories. County fixed effects and year fixed effects are included. Household weights are applied. Dollars are inflation-adjusted and based on 2010 dollars. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

3.10 Conclusion

We investigate how spouse bargaining power affects the household consumption of the married couples in the US by using spouse relative education and relative gender potential wage in the local labor market as two proxies for bargaining power. The literature on household economics suggests that an increase in women's wages or education relative to men's potentially improve wives' positions within households, resulting in different consumption patterns.

We find consistent results with this bargaining power explanation: households spend more on beauty goods, which are more preferred by women, and spend less on alcohol, which is more preferred by men, when relative education or potential wages of women increase. We also find a limited evidence that higher relative wages result in higher expenditure shares on frozen food. Given that women prefer healthier diet, this may seem surprising, but this may be explained by different labor market allocations due to changes in relative wages. Lastly, for couples with children, improved women's household bargaining position is associated with higher budget share on books, stationary, and school supplies, which are potentially related to investment in children. Our robustness checks show that these effects are not driven by income effects. Hence, our view is that the spouse bargaining position channel is most likely to drive our results.

References

Adda, J., P. Pinotti, and G. Tura (2022). "There is More to Marriage than Love: The Effect of Legal Status and Cultural Distance on Intermarriages and Separations". Working Paper.

Ahn, S. Y. (2022). "Matching Across Markets: An Economic Analysis of Cross-Border Marriage". Working Paper.

Aizer, A. (2010). "The Gender Wage Gap and Domestic Violence". In: *American Economic Review* 100.4, pp. 1847–1859.

Anderberg, D. and A. Vickery (2021). "The Role of Own-Group Density and Local Social Norms for Ethnic Marital Sorting: Evidence from the UK". In: *European Economic Review* 138.

Armand, A. et al. (2020). "The Effect of Gender-Targeted Cash Transfers on Household Expenditure: Evidence from a Randomized Experiment". In: *The Economic Journal* 130.631, pp. 1875–1897.

Attanasio, O. and V. Lechene (2014). "Efficient Responses to Targeted Cash Transfers". In: *Journal of Political Economy* 122.1, pp. 178–222.

Autor, D., D. Dorn, and G. Hanson (2019). "When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Men". In: *American Economic Review: Insights* 1.2, pp. 161–178.

Banks, Ralph Richard (2012). *Is Marriage for White People?: How the African American Marriage Decline Affects Everyone*. Dutton/Penguin Books.

Bartik, Timothy J. (1991). *Who Benefits from State and Local Economic Development Policies?* W.E. Upjohn Institute for Employment Research.

Basu, Kaushik and Ranjan Ray (2011). *The Collective Model of the Household and An Unexpected Implication for Child Labor: Hypothesis and an Empirical Test*. Allied Publishers.

Bayer, P. and K. K. Charles (2018). "Divergent Paths: A New Perspective on Earnings Differences Between Black and White Men Since 1940". In: *The Quarterly Journal of Economics* 133.3, pp. 1459–1501.

Bertrand, M. et al. (2021). "Social Norms, Labor Market Opportunities, and the Marriage Gap for Skilled Women". In: *Review of Economic Studies* 88.4, pp. 1936–78.

Bertrand, Marianne, Emir Kamenica, and Jessica Pan (2015). “Gender Identity and Relative Income within Households”. In: *The Quarterly Journal of Economics* 130.2, pp. 571–614.

Blanchard, Olivier Jean et al. (1992). “Regional Evolutions”. In: *Brookings Papers on Economic Activity* 1992.1, p. 1. DOI: 10.2307/2534556.

Browning, M., P-A Chiappori, and Y. Weiss (2014). *Economics of the Family*. Cambridge University Press.

Browning, Martin et al. (1994). “Income and Outcomes: A Structural Model of Intrahousehold Allocation”. In: *Journal of Political Economy* 102.6, pp. 1067–1096.

Budiman, A. and N. G. Ruiz (2021). *Key Facts about Asian Americans, a Diverse and Growing Population*. Tech. rep. Pew Research Center, Washington D.C. URL: https://www.pewresearch.org/fact-tank/2021/04/29/key-facts-about-asian-americans.

Calvi, Rossella (2020). “Why Are Older Women Missing in India? The Age Profile of Bargaining Power and Poverty”. In: *Journal of Political Economy* 128.7, pp. 2453–2501.

Calvo, P., I Lindenlaub, and L. Uniat (2021). “Intra Household Decision Making: New Evidence from the Innovation Sample of the German Socioeconomic Panel”. Working Paper.

Caucutt, E. M., N. Guner, and C. Rauh (2021). “Is Marriage for White People? Incarceration, Unemployment, and the Racial Marriage Divide”. HCEO Working Paper Series.

Charles, K. and M. C. Luoh (2010). “Male Incarceration, the Marriage Market, and Female Outcomes”. In: *The Review of Economics and Statistics* 92.3, pp. 614–627.

Charles, K. K. and J. Guryan (2008). “Prejudice and Wages: An Empirical Assessment of Becker’s the Economics of Discrimination”. In: *Journal of Political Economy* 116.5, pp. 773–809.

Chernozkukhov, Victor and Christian Hansen (2008). “The reduced form: A simple approach to inference with weak instruments”. In: *Economic Letters* 100, pp. 68–71.

Chiappori, P-A, M. Costa Dias, and C. Meghir (2020). “Changes in Assortative Matching: Theory and Evidence for the US”. In: *NBER Working Paper* 26943.

Chiappori, P-A, B. Fortin, and G. Lacroix (2002). “Marriage Market, Divorce Legislation, and Household Labor Supply”. In: *Journal of Political Economy* 110.1, pp. 37–72.

Chiappori, P. A., Murat Iyigun, and Yoram Weiss (2009). “Investment in Schooling and the Marriage Market”. In: *American Economic Review* 99.5, pp. 1689–1713.

Chiappori, P-A and B. Salanié (2016). “The Econometrics of Matching Models”. In: *Journal of Economic Literature* 54.3, pp. 832–861.

Chiappori, P-A, B. Salanié, and Y. Weiss (2017). “Partner Choice, Investment in Children, and the Marital College Premium”. In: *American Economic Review* 107.7, pp. 2109–2167.

Chiappori, P.-A. et al. (2022). “Assortative Matching on Income”. Working Paper.

Chiappori, Pierre-Andre (2017). *Matching with Transfers: The Economics of Love and Marriage*. Princeton University Press.

Choo, E. and A. Siow (2006). “Who Marries Whom and Why”. In: *Journal of Political Economy* 114.1, pp. 175–201.

Chuan, A. and W. Zhang (2022). “Non-College Occupations, Workplace Routinization, and the Gender Gap in College Enrollment”. Working Paper.

Ciscato, E. and S. Weber (2020). “The Role of Evolving Marital Preferences in Growing Income Inequality”. In: *Journal of Population Economics* 33, pp. 307–347.

Davern, M. et al. (2021). *General Social Surveys, 1972-2021 Cross-section [machine-readable data file, 68,846 cases]*. Tech. rep. NORC at the University of Chicago. URL: `gssdataexplorer.norc.org`.

Duflo, E. (2003). “Grandmothers and Granddaughters: Old-Age Pensions and Intrahousehold Allocation in South Africa”. In: *The World Bank Economic Review* 17.1, pp. 1–25.

Dunbar, Geoffrey R, Arthur Lewbel, and Krishna Pendakur (2013). “Childrens Resources in Collective Households: Identification, Estimation, and an Application to Child Poverty in Malawi”. In: *American Economic Review* 103.1, pp. 438–471. DOI: `10.1257/aer.103.1.438`.

Duncan, B. and T. Trejo (2011). “Intermarriage and the Intergenerational Transmission of Ethnic Identity and Human Capital for Mexican Americans”. In: *Journal of Labor Economics* 29.2, pp. 195–227.

Dupuy, A. and A. Galichon (2014). “Personality Traits and the Marriage Market”. In: *Journal of Political Economy* 112, pp. 1271–1319.

Erten, Bilge and Pinar Keskin (2021). “Trade-offs? The Impact of WTO Accession on Intimate Partner Violence in Cambodia”. In: *Working Paper*.

Fisman, R. et al. (2008). “Racial Preferences in Dating”. In: *Review of Economic Studies* 75, pp. 117–132.

Flores, A. (2017). *How the U.S. Hispanic Population is Changing*. Tech. rep. Pew Research Center, Washington D.C. URL: https://www.pewresearch.org/fact-tank/2017/09/18/how-the-u-s-hispanic-population-is-changing.

Fryer Jr., R. G. (2007). “Guess Who’s Been Coming to Dinner? Trends in Interracial Marriage over the 20th Centry”. In: *Journal of Economic Perspectives* 21.2, pp. 71–90.

Fu, X. and T. B. Heaton (2008). “Racial and Educational Homogamy: 1980 to 2000”. In: *Sociological Perspectives* 51.4, pp. 735–758.

Furtado, Delia (2015). “Ethnic Intermarriage”. In: *International Encyclopedia of the Social & Behavioral Sciences*, pp. 118–122. DOI: 10.1016/b978-0-08-097086-8.31097-2.

Gale, D. and L. Shapley (1962). “College Admissions and the Stability of Marriage”. In: *American Mathematical Monthly* 61.1, pp. 9–15.

Galichon, A. and B. Salanié (2022). “Cupid’s Invisible Hand: Social Surplus and Identification in Matching Models”. In: *Review of Economic Studies* 89.5, pp. 2600–2629.

Goldin, C., L. Katz, and I. Kuziemko (2006). “The Home Coming of American College Women: The Reversal of the College Gender Gap”. In: *Journal of Economic Perspectives* 20.4, pp. 133–156.

Goldsmith-Pinkham, Paul, Issac Sorkin, and Henry Swift (2020). “Bartik Instruments: What, When, Why, and How”. In: *American Economic Review* 110.8, pp. 2586–2624.

Hitsch, G., A. Hortacsu, and D. Ariely (2010). “Matching and Sorting in Online Dating”. In: *American Economic Review* 100.1, pp. 130–163.

Hoddinott, J. and L. Haddad (1995). “Does Female Income Share Influence Household Expenditure? Evidence from Cote D’Ivoire”. In: *Oxford Bulletin of Economics and Statistics* 57.1, pp. 77–96.

Hoehn-Velasco, L. and J. Penglase (2021). “Changes in Assortative Matching and Educational Inequality: Evidence from Marriage and Birth Records in Mexico”. In: *Journal of Demographic Economics (Forthcoming)*.

Judd, Kenneth L. (1998). *Numerical Methods in Economics*. MIT Press.

Kalmijn, M. (1991). “Status Homogamy in the United States”. In: *Annual Journal of Sociology* 97.2, pp. 496–523.

— (2010). “Consequences of Racial Intermarriage for Children’s Social Integration”. In: *Sociological Perspectives* 53.2, pp. 271–86.

Kearney, M. S. and R. Wilson (2018). “Male Earnings, Marriageable Men, and Nonmarital Fertility: Evidence from the Fracking Boom”. In: *The Review of Economics and Statistics* 100.4, pp. 678–690.

Koh, Y. K. (2022). “The Unequal Gains from Racial Desegregation in the US Marriage Market”. Working Paper.

Lewbel, Arthur and Krishna Pendakur (2008). “Estimation of collective household models with Engel curves”. In: *Journal of Econometrics* 147.2, pp. 350–358.

Lichter, D. T., J. H. Carmalt, and Z. Qian (2011). “Immigration and Intermarriage Among Hispanics: Crossing Racial and Generational Boundaries”. In: *Sociological Forum* 26.2, pp. 241–264.

Lin, K-H. and J. Lundquist (2013). “Male Selection in Cyberspace: The Intersection of Race, Gender, and Education”. In: *American Journal of Sociology* 119.1, pp. 183–215.

Liu, S. (2020). “Incarceration of African American Men and the Impacts on Women and Children”. Working Paper.

Livingston, G. and A. Brown (2017). *Intermarriage in the U.S. 50 Years After Loving v. Virginia*. Tech. rep. Pew Research Center, Washington D.C. URL: `https://www.pewsocialtrends.org/2017/05/18/intermarriage-in-the-u-s-50-years-after-loving-v-virginia/`.

Lopez, M. H., J. M. Krogstad, and J. S. Passel (2022). *Who is Hispanic?* Tech. rep. Pew Research Center, Washington D.C. URL: `https://www.pewresearch.org/fact-tank/2022/09/15/who-is-hispanic`.

Lundberg, S., R. A. Pollak, and J. Stearns (2016). “Family Inequality: Diverging Patterns in Marriage, Cohabitation, and Childbearing”. In: *Journal of Economic Perspectives* 30.2, pp. 79–102.

Lundberg, S. J., R. A. Pollak, and T. J. Wales (1997). “Do Husbands and Wives Pool Their Resources? Evidence from the United Kingdom Child Benefit”. In: *The Journal of Human Resources* 32.3, pp. 463–480.

Lundberg, Shelly and Robert A Pollak (1993). “Separate Spheres Bargaining and the Marriage Market”. In: *Journal of Political Economy* 101.6, pp. 988–1010.

Merlino, L. P., M. F. Steinhardt, and L. Wren-Lewis (2019). “More than Just Friends? School Peers and Adult Interracial Relationships”. In: *Journal of Labor Economics* 37.3, pp. 663–713.

Mourifié, I. and A. Siow (2021). “The Cobb Douglas Marriage Matching Function: Marriage Matching with Peer and Scale Effects”. In: *Journal of Labor Economics* 39.51, pp. 239–274.

O'Flaherty, Brendan (2015). *The Economics of Race in the United States*. Harvard University Press.

Phipps, S. A. and P. S. Burton (1998). "What's Mine is Yours? The Influence of Male and Female Incomes on Patterns of Household Expenditure". In: *Economica* 65.260, pp. 599–613.

Qian, Z. and D. T. Lichter (2011). "Changing Patterns of Interracial Marriage in a Multiracial Society". In: *Journal of Marriage and Family* 73.5, pp. 105–1084.

Quisumbing, Agnes R and John A Maluccio (2003). "Resources at Marriage and Intrahousehold Allocation: Evidence from Bangladesh, Ethiopia, Indonesia, and South Africa". In: *Oxford Bulletin of Economics and Statistics* 65.3, pp. 283–327.

Ruggles, S. et al. (2022). *IPUMS USA: Version 12.0 [dataset]*. Tech. rep. Minneapolis, MN: IPUMS. URL: https://doi.org/10.18128/D010.V12.0.

Schaner, Simone (2017). "The cost of convenience? Transaction costs, bargaining power, and savings account use in Kenya". In: *Journal of Human Resources* 52.4, pp. 919–945.

Schwartz, C. R. (2013). "Trends and Variation in Assortative Mating: Causes and Consequences". In: *Annual Review of Sociology* 39, pp. 451–70.

Shapley, L. and M. Shubik (1971). "The Assignment Game I: The Core". In: *International Journal of Game Theory* 1.1, pp. 111–130.

Shenhav, N. (2021). "Lowering Standards to Wed? Spouse Quality, Marriage, and Labor Market Responses to the Gender Wage Gap". In: *The Review of Economics and Statistics* 103.2, pp. 265–279.

Stewart, D. M. (2020). *Black Women, Black Love: America's War on African American Marriage*. Seal Press, Hachette Book Group.

Thomas, D. (1990). "Intra-Household Resource Allocation: An Inferential Approach". In: *The Journal of Human Resources* 25.4, pp. 635–664.

Ward-Batts, J. (2008). "Out of the Wallet and into the Purse: Using Micro Data to Test Income Pooling". In: *Journal of Human Resources* 43.2, pp. 325–351.

Appendix A: Appendix to Chapter 1

A.1 Appendix: Tables and Figures

A.1.1 Additional Tables

Table A.1: Percentage of Other Race and Mixed Races in Each Census Year, Female Aged 35-44, Male Aged 37-46

Year	Other Race	Mixed Race
1980	0.71%	N/A
1990	0.78%	N/A
2000	0.88%	2.12%
2010	0.92%	1.65%
2019	0.89%	2.55%

Notes: This table presents the proportion of people who reported Other Race (which includes "American Indian or Alaska Native" and "Other race") and Mixed Race among women aged 35-44 and men aged 37-46 for each survey year. A response option of mixed race was added from the 2000 census and onwards. Data sources for this table are: 1960 5% sample Census, 1970 1% sample Census, 1980 5% sample Census, 1990 5% sample Census, 2000 5% sample Census, 2010 5% sample American Community Survey (2006-2010 5 year pooled sample), 2019 5% sample American Community Survey (2005-2019 5 year pooled sample). Survey weight is applied.

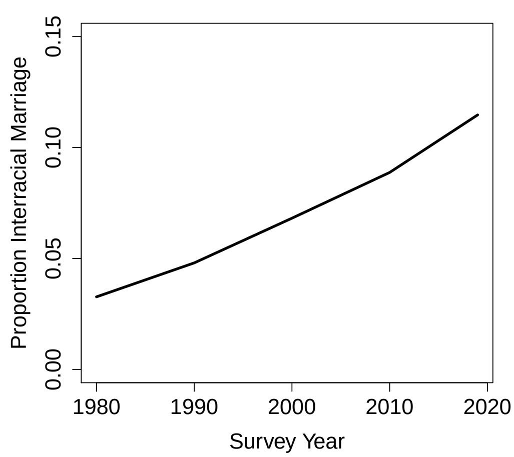
Table A.2: Percentage of Never Married Singles who Cohabit in Each Census Year, Female Aged 35-44, Male Aged 37-46

Year	% Cohabiting
1990	11.3%
2000	17.7%
2010	21.3%
2019	24.6%

Notes: This table presents the proportion of respondents who reported to have cohabiting partners among never-married single women aged 35-44 and never-married single men aged 37-46 for each survey year. A response option for a cohabiting partner was added from the 1990 census and onwards. Data sources for this table are: 1990 5% sample Census, 2000 5% sample Census, 2010 5% sample American Community Survey (2006-2010 5 year pooled sample), 2019 5% sample American Community Survey (2005-2019 5 year pooled sample).

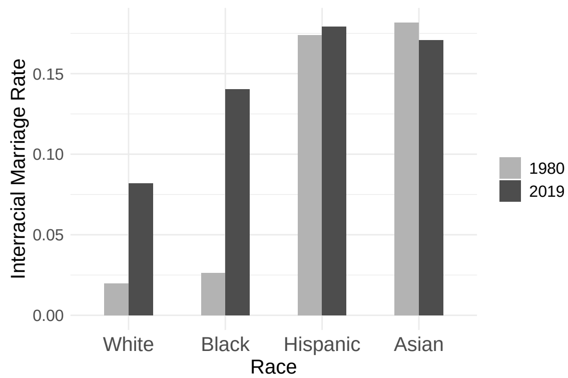
A.1.2 Additional Figures

Figure A.1: Interracial Marriage Rate, Among Married, Age 35-44



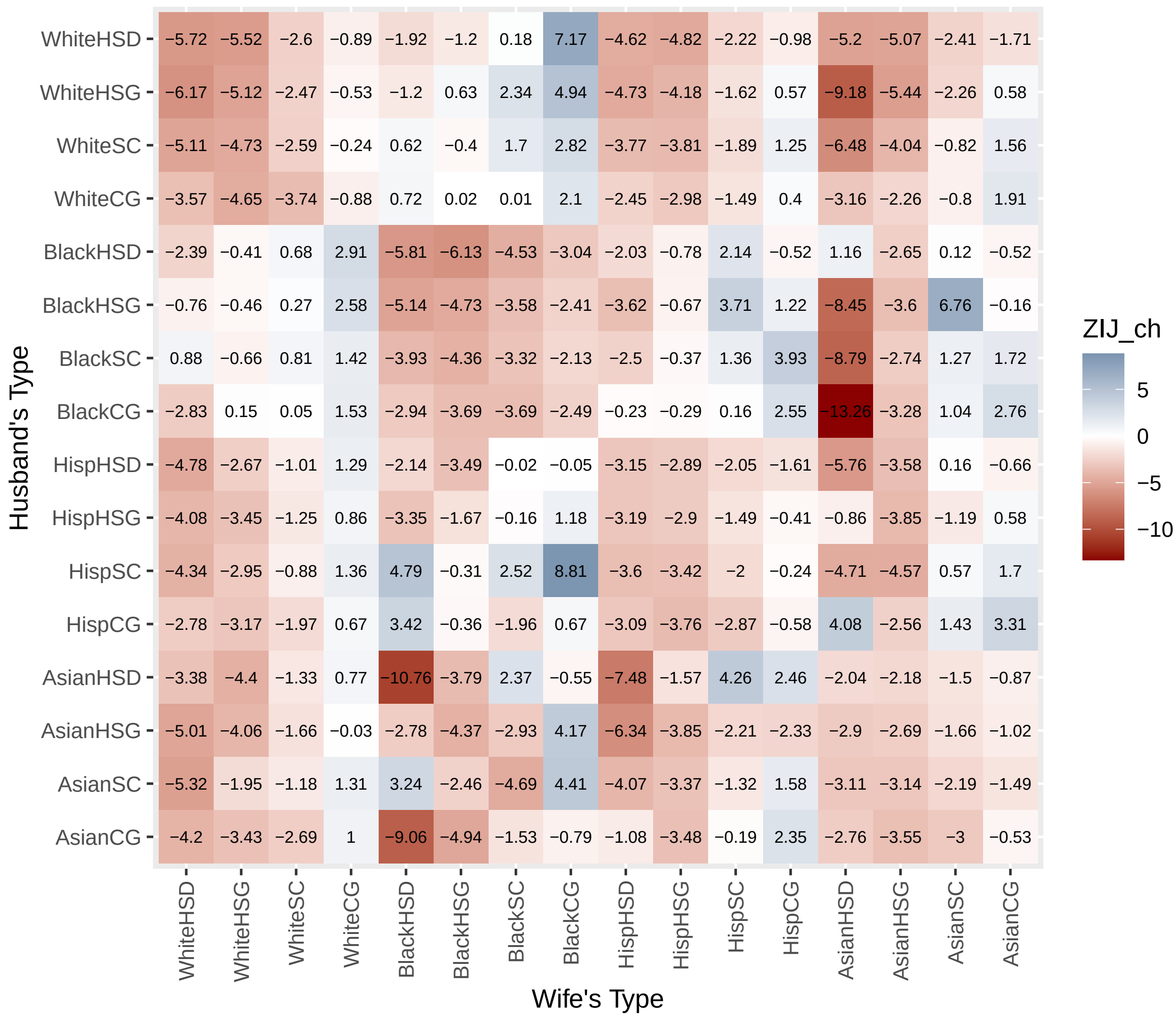
Note: This figure shows the proportion of interracial marriage among married men and women aged 35-44 for each survey year. Data sources for this figure are: 1960 5% sample Census, 1970 1% sample Census, 1980 5% sample Census, 1990 5% sample Census, 2000 5% sample Census, 2010 5% sample American Community Survey (2006-2010 5 year pooled sample), 2019 5% sample American Community Survey (2005-2019 5 year pooled sample). For Hispanics, 1960 and 1970 are excluded as the Hispanic identification is imputed by the IPUMS and does not properly capture the interracial marriage with non-Hispanic whites. Survey weight is applied.

Figure A.2: Interracial/Interethnic Marriage For Each Race/Ethnicity, Among Married, Age 35-44



Note: This figure shows the proportion of those who married out of their race/ethnicity among married men and women aged 35-44 in 1980 and in 2019, respectively. Data sources for this figure are: 1980 5% sample Census microdata and 2019 5% sample American Community Survey (2015-2019 5-year pooled sample). Survey weight is applied.

Figure A.3: Changes in Marital Surplus Z^{IJ} from 1980 to 2019

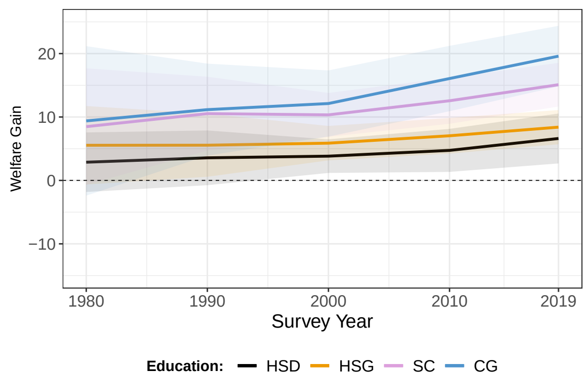


Note: This figure shows the heatmap for the change in estimated marital surplus $\hat{Z}_t^{IJ}$ from year 1980 to 2019. Data used to estimate this matrix is described in Section 3.3. I refers to husband's type (Row) and J refers to wife's type (Column). A note of caution is that the magnitudes of these differences are not comparable with each other. This is because the Z_t^{IJ} is a nonlinear log function as shown in Equation (1.5) so that we cannot compare the magnitudes of the changes in Z_t^{IJ} with different starting values. Hence, I only focus on the sign of each change, rather than on the magnitude of each change.

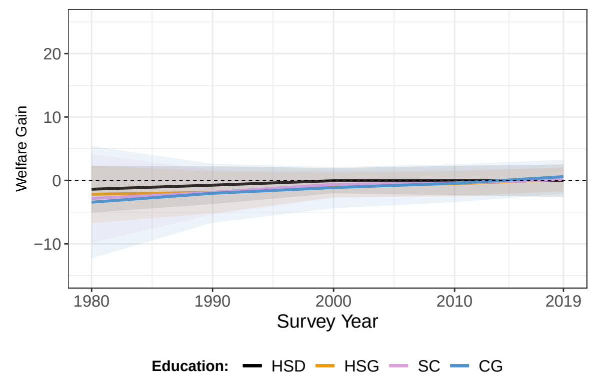
A.1.3 Sensitivity Check: Excluding Cohabiting Singles

As shown in Table A.2, the proportion of never-married singles who cohabit with a partner has increased over time. To see how the cohabiting singles affect the results, I perform sensitivity analyses that exclude cohabiting singles from the single population. I re-estimate the welfare gains from marital desegregation for each group, which is presented in Figure A.4. The results confirm that excluding cohabiting singles do not affect the results for welfare gain from marital desegregation.

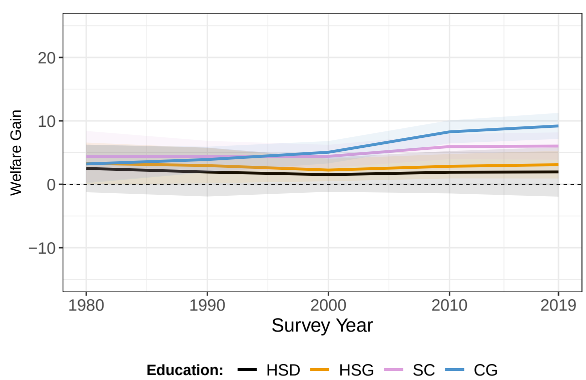
Figure A.4: Type-Specific Welfare Gains from Marital Desegregation, Excluding Cohabiting Singles



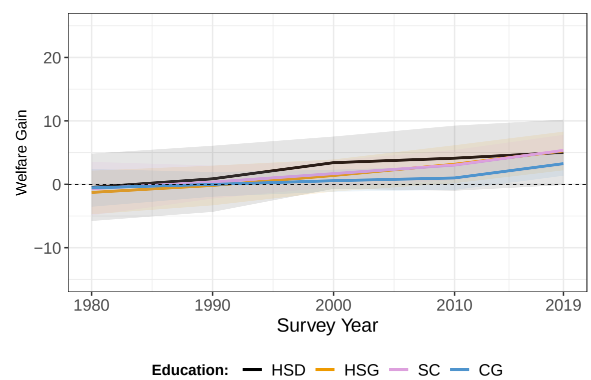
(a) Black Men



(b) Black Women



(c) White Men



(d) White Women

Note: These figures plot the welfare gains from marital desegregation as defined by Equation (1.10) and Equation (1.11) for each specified type of men and women. Data used to calculate the gains are: 1980-2000 Decennial Census, 2010 and 2019 5-Year ACS. I focus on age 37-46 men and age 35-44 women for each survey year. Further details on the sample restriction are described in Section 3.3. I exclude cohabiting singles from the estimation sample. Shade for each line refers to the 95% confidence interval. Standard errors are calculated from the sampling variation in the data.

A.2 Appendix: Decomposition

A.2.1 Full Solution of IFT Partials

Full solution for the IFT partials: Full solution for the Jacobian matrix (Equation 1.14) is as follows:

$$\left[\frac{\partial \mathbf{s}}{\partial \tilde{\boldsymbol{\theta}}}\right]_{(2K)\times(2K+K^2)} = -\underbrace{\begin{bmatrix} \dfrac{\partial \mathbf{F}}{\partial \mathbf{s}} \\ \\ \dfrac{\partial \mathbf{G}}{\partial \mathbf{s}} \end{bmatrix}^{-1}_{(2K)\times(2K)}}_{[A]} \underbrace{\begin{bmatrix} \dfrac{\partial \mathbf{F}}{\partial \tilde{\boldsymbol{\theta}}} \\ \\ \dfrac{\partial \mathbf{G}}{\partial \tilde{\boldsymbol{\theta}}} \end{bmatrix}_{(2K)\times(2K+K^2)}}_{[B]}$$

where

$$[A] = \begin{bmatrix} 2s_{1\emptyset} + \sum_J \tilde{Z}_{1J} s_{\emptyset J} & 0 & \cdots & 0 & \tilde{Z}_{11} s_{1\emptyset} & \tilde{Z}_{12} s_{1\emptyset} & \cdots & \tilde{Z}_{1K} s_{1\emptyset} \\ 0 & 2s_{2\emptyset} + \sum_J \tilde{Z}_{2J} s_{\emptyset J} & \cdots & 0 & \tilde{Z}_{21} s_{2\emptyset} & \tilde{Z}_{22} s_{2\emptyset} & \cdots & \tilde{Z}_{2K} s_{2\emptyset} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & 2s_{K\emptyset} + \sum_J \tilde{Z}_{KJ} s_{\emptyset J} & \tilde{Z}_{K1} s_{K\emptyset} & \tilde{Z}_{K2} s_{K\emptyset} & \cdots & \tilde{Z}_{KK} s_{K\emptyset} \\ \tilde{Z}_{11} s_{\emptyset 1} & \tilde{Z}_{21} s_{\emptyset 1} & \cdots & \tilde{Z}_{K1} s_{\emptyset 1} & 2s_{\emptyset 1} + \sum_I \tilde{Z}_{I1} s_{I\emptyset} & 0 & \cdots & 0 \\ \tilde{Z}_{12} s_{\emptyset 2} & \tilde{Z}_{22} s_{\emptyset 2} & \cdots & \tilde{Z}_{K2} s_{\emptyset 2} & 0 & 2s_{\emptyset 2} + \sum_I \tilde{Z}_{I2} s_{I\emptyset} & \cdots & 0 \\ \vdots & \vdots & & \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{Z}_{1K} s_{\emptyset K} & \tilde{Z}_{2K} s_{\emptyset K} & \cdots & \tilde{Z}_{KK} s_{\emptyset K} & 0 & 0 & \cdots & 2s_{\emptyset K} + \sum_I \tilde{Z}_{IK} s_{I\emptyset} \end{bmatrix}^{-1}$$

and

$$
[B] = \begin{bmatrix}
-1 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & s_{1\emptyset}s_{\emptyset 1} & s_{1\emptyset}s_{\emptyset 2} & \cdots & s_{1\emptyset}s_{\emptyset K} & 0 & 0 & \cdots & 0 & \cdots & 0 & \cdots & 0 \\
0 & -1 & \cdots & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & s_{2\emptyset}s_{\emptyset 1} & s_{2\emptyset}s_{\emptyset 2} & \cdots & s_{2\emptyset}s_{\emptyset K} & \cdots & 0 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots & & \vdots & \vdots & \vdots & & \vdots & \vdots & \vdots & & \vdots & & \vdots & & \vdots \\
0 & 0 & \cdots & -1 & 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & 0 & \cdots & s_{K\emptyset}s_{\emptyset 1} & \cdots & s_{K\emptyset}s_{\emptyset K} \\
0 & 0 & \cdots & 0 & -1 & 0 & \cdots & 0 & s_{1\emptyset}s_{\emptyset 1} & 0 & \cdots & 0 & s_{2\emptyset}s_{\emptyset 1} & 0 & \cdots & 0 & \cdots & s_{K\emptyset}s_{\emptyset 1} & \cdots & 0 \\
0 & 0 & \cdots & 0 & 0 & -1 & \cdots & 0 & 0 & s_{1\emptyset}s_{\emptyset 2} & \cdots & 0 & 0 & s_{2\emptyset}s_{\emptyset 2} & \cdots & 0 & \cdots & 0 & \cdots & 0 \\
\vdots & \vdots & & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & 0 & 0 & 0 & \cdots & -1 & 0 & 0 & \cdots & s_{1\emptyset}s_{\emptyset K} & 0 & 0 & \cdots & s_{2\emptyset}s_{\emptyset K} & \cdots & 0 & \cdots & s_{K\emptyset}s_{\emptyset K}
\end{bmatrix}
$$

Estimation of the Jacobian matrix is done by combining [A] and [B] using matrix multiplication.

A.2.2 Details on Decomposition Procedures

In this section, I describe the estimation steps to decompose the expected utility of type I men. The application to the welfare gain, which is a function of expected utilities, can be done analogously.

STEP 1: First, to link the change in the expected utility to the IFT partials, I take the total differential of the expected utility:

$$d\bar{u}^I = \frac{1}{n^I} dn^I - \frac{2}{s^{I\emptyset}} \Big(\underbrace{\frac{\partial s^{I\emptyset}}{\partial \tilde{\boldsymbol{\theta}}}}_{From\ IFT} d\tilde{\boldsymbol{\theta}} \Big) \tag{A.1}$$

STEP 2: A naive way of expressing the changes in $\bar{u}^I$ from year 1980 to 2019 using Equation (1.15) is the following:

$$\Delta^{2019-1980}\bar{u}^I = \frac{1}{n^I}\Delta^{2019-1980}n^I - \frac{2}{s^{I\emptyset}}\Big(\frac{\partial s^{I\emptyset}}{\partial \tilde{\boldsymbol{\theta}}}\Delta^{2019-1980}\tilde{\boldsymbol{\theta}}\Big)$$

where $\Delta^{2019-1980}y$ refers to change in y from 1980 to 2019. However, this is problematic because the implicit function theorem and the total differentials only give good approximations for *very small* changes in the model primitives. US has experienced large changes in population distribution over the past four decades. Moreover, marital surplus $\mathbf{Z}$ also has experienced changes over time. Hence, it is improper to use 40 years of changes to evaluate Equation (A.1).

A better, but still not ideal, approach is to divide the time period into smaller time periods based on available survey years. Because I use the census data with 10-year intervals, $\Delta^{2019-1980}\bar{u}^I_t$ can be decomposed into:

$$\Delta^{2019-1980}\bar{u}^I = \Delta^{1990-1980}\bar{u}^I + \Delta^{2000-1990}\bar{u}^I + \Delta^{2010-2000}\bar{u}^I + \Delta^{2019-2010}\bar{u}^I$$

However, changes in model primitives over each decade may still be considered large.

In order to better approximate the effect of changes in model primitives on $d\bar{u}^I_t$, I implement the homotopy method following Judd, 1998. This method decomposes the large changes in the model primitives into a series of infinitesimal changes. I apply this method for each decade based on the available survey years: 1980 to 1990, 1990 to 2000, 2000 to 2010, and 2010 to 2019.

To give a concrete example, I consider the changes from 1980 to 1990. Let me denote 1980 as $\tau = 0$ and 1990 as $\tau = 1$. Then $\tilde{\boldsymbol{\theta}}_0$ (resp. $\tilde{\boldsymbol{\theta}}_1$) is the vector of the values of model primitives in 1980 (resp. in 1990). Then I consider the homotopy:

$$\tilde{\boldsymbol{\theta}}_\tau = \tau\tilde{\boldsymbol{\theta}}_1 + (1-\tau)\tilde{\boldsymbol{\theta}}_0, \quad \tau \in [0, 1]$$

which defines a series of intermediate values of the model primitives with interval $d\tau$ between observed values at $\tau = 0$ and $\tau = 1$. Because $\tilde{\boldsymbol{\theta}}_\tau$ is now a function of τ as defined above, $d\tilde{\boldsymbol{\theta}}_\tau$ becomes $d\tilde{\boldsymbol{\theta}}_\tau = (\tilde{\boldsymbol{\theta}}_1 - \tilde{\boldsymbol{\theta}}_0)d\tau$. Then, applying the homotopy to Equation (A.1),

$$d\bar{u}^I = \frac{1}{n_\tau^I}(n_1^I - n_0^I)d\tau - \frac{2}{s^{I\emptyset}}\left(\left[\frac{\partial s^{I\emptyset}}{\partial\tilde{\boldsymbol{\theta}}_\tau}\right]_\tau(\tilde{\boldsymbol{\theta}}_1 - \tilde{\boldsymbol{\theta}}_0)d\tau\right) \tag{A.2}$$

where $\left[\frac{\partial s^{I\emptyset}}{\partial\tilde{\theta}_t}\right]_\tau$ means that this partial is evaluated at each τ. Note that $s_\tau^{I\emptyset}$ is updated as τ progresses with interval $d\tau$.

I use Equation (A.2) to estimate $d\bar{u}^I$ for each decade and to decompose $d\bar{u}^I$ into contributions by change in each of the model primitives. With the homotopy method, I can use infinitesimal change dt to evaluate and decompose $\Delta^{(\tau+d\tau)-\tau}\bar{u}^I$ for $\tau \in [0, 1]$. I specify $d\tau = 0.001$ when estimating Equation (A.2) for each decade. Summing $\Delta^{(\tau+d\tau)-\tau}\bar{u}^I$ over all $\tau \in [0, 1]$ gives better approximation of $\Delta\bar{u}^I$ than using the observed 10-year changes of model primitives to evaluate Equation (A.1).

For a more concrete illustration, I describe in detail how I perform first few steps for this fine-tuning method:

- **STEP 2.1:** From $\tau = 0 \rightarrow \tau = 0.001$

The goal is to estimate $\bar{u}^I_{0.001}$. Starting from $\bar{u}^I_0$,

$$\bar{u}^I_{0.001} = \bar{u}^I_0 + d\bar{u}^I_0$$

Using the fine-tuning method, $d\bar{u}^I_0$ is expressed as:

$$d\bar{u}^I_0 = \frac{1}{n^I_0}(n^I_1 - n^I_0) \cdot 0.001 - \frac{2}{s^{I\emptyset}_0}\frac{\partial s^{I\emptyset}_0}{\partial \tilde{\boldsymbol{\theta}}_\tau}(\tilde{\boldsymbol{\theta}}_1 - \tilde{\boldsymbol{\theta}}_0) \cdot 0.001$$

Note that $\frac{\partial s^{I\emptyset}_0}{\partial \tilde{\boldsymbol{\theta}}_\tau}$ is a function of $s^{I\emptyset}_0$, $s^{\emptyset J}_0$, Z^{IJ}_0, all of which are evaluated at $\tau = 0$.

In this step, I also need to compute $s^{I\emptyset}_{0.001}$ and $s^{\emptyset J}_{0.001}$, because these will be used in the next step. For example,

$$\begin{aligned} s^{I\emptyset}_{0.001} &= s^{I\emptyset}_0 + ds^{I\emptyset}_0 \\ &= s^{I\emptyset}_0 + \frac{\partial s^{I\emptyset}_0}{\partial \tilde{\boldsymbol{\theta}}_\tau}(\tilde{\boldsymbol{\theta}}_1 - \tilde{\boldsymbol{\theta}}_0) \cdot 0.001 \end{aligned}$$

- **STEP 2.2:** From $\tau = 0.001 \to \tau = 0.002$.

The goal is to estimate $\bar{u}^I_{0.002}$. Starting from $\bar{u}^I_{0.001}$,

$$\bar{u}^I_{0.002} = \bar{u}^I_{0.001} + d\bar{u}^I_{0.001}$$

Using the fine-tuning method, $d\bar{u}^I_{0.001}$ is expressed as:

$$d\bar{u}^I_{0.001} = \frac{1}{n^I_{0.001}}(n^I_1 - n^I_0) \cdot 0.001 - \frac{2}{s^{I\emptyset}_{0.001}}\frac{\partial s^{I\emptyset}_{0.001}}{\partial \tilde{\boldsymbol{\theta}}_\tau}(\tilde{\boldsymbol{\theta}}_1 - \tilde{\boldsymbol{\theta}}_0) \cdot 0.001$$

where $n^I_{0.001} = 0.001 n^I_1 + 0.999 n^I_0$.

Note that $\frac{\partial s^{I\emptyset}_{0.001}}{\partial \tilde{\boldsymbol{\theta}}_\tau}$ is a function of $s^{I\emptyset}_{0.001}$, $s^{\emptyset J}_{0.001}$, and $Z^{IJ}_{0.001}$. I have already estimated $s^{I\emptyset}_{0.001}$ and $s^{\emptyset J}_{0.001}$ from the previous step, and $Z^{IJ}_{0.001} = 0.001 Z^{IJ}_1 + 0.999 Z^{IJ}_0$.

In this step, I also need to compute $s^{I\emptyset}_{0.002}$ and $s^{\emptyset J}_{0.002}$, because these will be used in the next step. For example,

$$\begin{aligned} s^{I\emptyset}_{0.002} &= s^{I\emptyset}_{0.001} + ds^{I\emptyset}_{0.001} \\ &= s^{I\emptyset}_{0.001} + \frac{\partial s^{I\emptyset}_{0.001}}{\partial \tilde{\boldsymbol{\theta}}_\tau}(\tilde{\boldsymbol{\theta}}_1 - \tilde{\boldsymbol{\theta}}_0) \cdot 0.001 \end{aligned}$$

- **STEP 2.3 and above:** The rest of the estimation proceeds analogously until τ reaches 1.

STEP 3: I now explain how to decompose the changes from 1980 to 2019 in individual expected utilities $\bar{u}^I$ into contributions by each model primitive. As an example, let's consider how $\Delta^{1990-1980}\bar{u}^I$ is estimated according to Equation (A.2):

$$\Delta^{1990-1980}\bar{u}^I = \sum_{\tau\in[0,1], d\tau=0.001} \frac{1}{n^I_\tau}(n^I_1 - n^I_0)d\tau - \frac{2}{s^{I\emptyset}}\left(\left[\frac{\partial s^{I\emptyset}}{\partial \tilde{\boldsymbol{\theta}}_\tau}\right]_\tau (\tilde{\boldsymbol{\theta}}_1 - \tilde{\boldsymbol{\theta}}_0)d\tau\right)$$

where $\tau = 0$ refers to year 1980 and $\tau = 1$ refers to year 1990.

Because $\Delta^{1990-1980}\bar{u}^I$ is a linear function in $(\tilde{\theta}_1 - \tilde{\theta}_0)$, it can be linearly decomposed into parts that are attributed to each model primitive θ^k.[1] I call this the **contribution** of θ^k to $\Delta^{1990-1980}\bar{u}^I$. The contribution of θ^k is essentially the change in θ^k from 1980 to 1990 multiplied by a multiplier that measures how sensitive $\bar{u}^I$ is with respect to the change in θ^k. Because summing up all contributions of the model primitives leads to $\Delta^{1990-1980}\bar{u}^I$, each contribution can be thought of as a portion of the changes in the expected utilities that is attributed to θ^k. In order to decompose changes in $\bar{u}^I$ over a longer time frame from 1980 to 2019, I simply sum up all four decade-by-decade contributions of each model primitive.

While I only described the decomposition steps for $\bar{u}^I$ for the illustration purpose, the decomposition for the welfare gains, which is $\bar{u}^{I,actual} - \bar{u}^{I,counterfactual}$, is straightforward.

[1] For example, the part of $\Delta^{1990-1980}\bar{u}^I$ that is contributed by the number of $WhiteHSG$ women is $\sum_{\tau\in[0,1], d\tau=0.001} -\frac{2}{s^{I\emptyset}}\left(\left[\frac{\partial s^{I\emptyset}}{\partial m^{WhiteHSG}_\tau}\right]_\tau (m^{WhiteHSG}_1 - m^{WhiteHSG}_0)d\tau\right)$.

A.2.3 More decomposition results

Table A.3: Decomposition: Top three contribution from changes in **Z**, Black HSG Men

		(1)	(2)	(3)
Contribution	Top (+)	1.1 $Z^{WhiteHSG,WhiteHSG}$	0.7 $Z^{BlackHSG,WhiteCG}$	0.6 $Z^{WhiteSC,WhiteHSG}$
	Top (-)	-0.6 $Z^{BlackHSG,AsianHSD}$	-0.4 $Z^{BlackHSG,WhiteHSG}$	-0.4 $Z^{BlackHSG,HispHSD}$

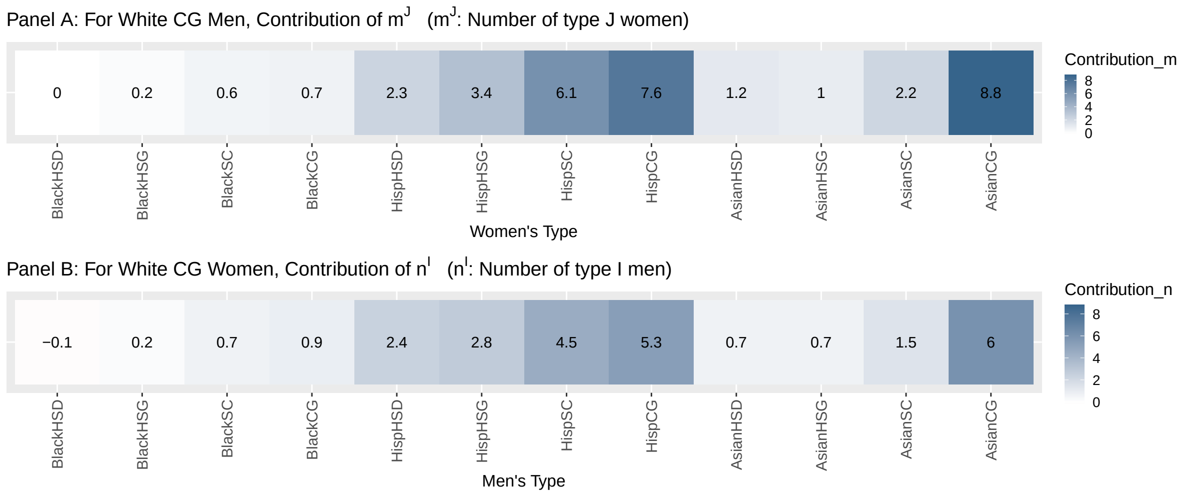
Notes: This table presents the top three positive and negative contributions from marital surplus to the 1980-2019 changes in the welfare gains from marital desegregation for Black HSG men. For marital surplus Z^{IJ}, I refers to husband's type and J refers to wife's type.

Table A.4: Decomposition: Top three contribution from changes in **Z**, Black HSG Women

		(1)	(2)	(3)
Contribution	Top (+)	1.5 $Z^{BlackHSG,BlackHSG}$	1.2 $Z^{BlackSC,BlackHSG}$	0.7 $Z^{BlackHSD,BlackHSG}$
	Top (-)	-0.2 $Z^{WhiteCG,WhiteSC}$	-0.2 $Z^{BlackHSG,BlackHSD}$	-0.2 $Z^{BlackSC,BlackSC}$

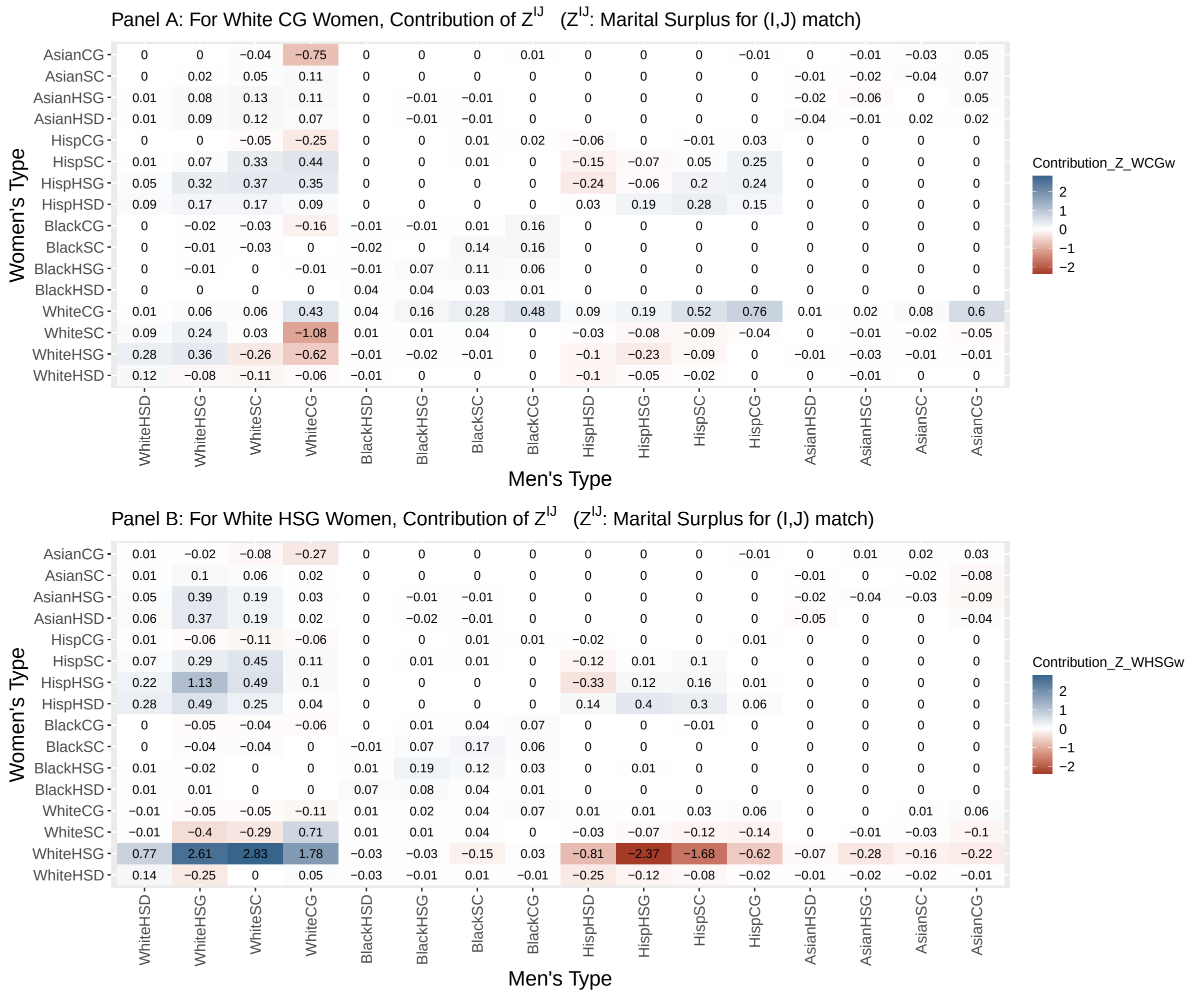
Notes: This table presents the top three positive and negative contributions from marital surplus to the 1980-2019 changes in the welfare gains from marital desegregation for Black HSG women. For marital surplus Z^{IJ}, I refers to husband's type and J refers to wife's type.

Figure A.5: Contribution of Each Population Primitive to the 1980-2019 Change in the Welfare Gains, For White CG Men and White CG Women



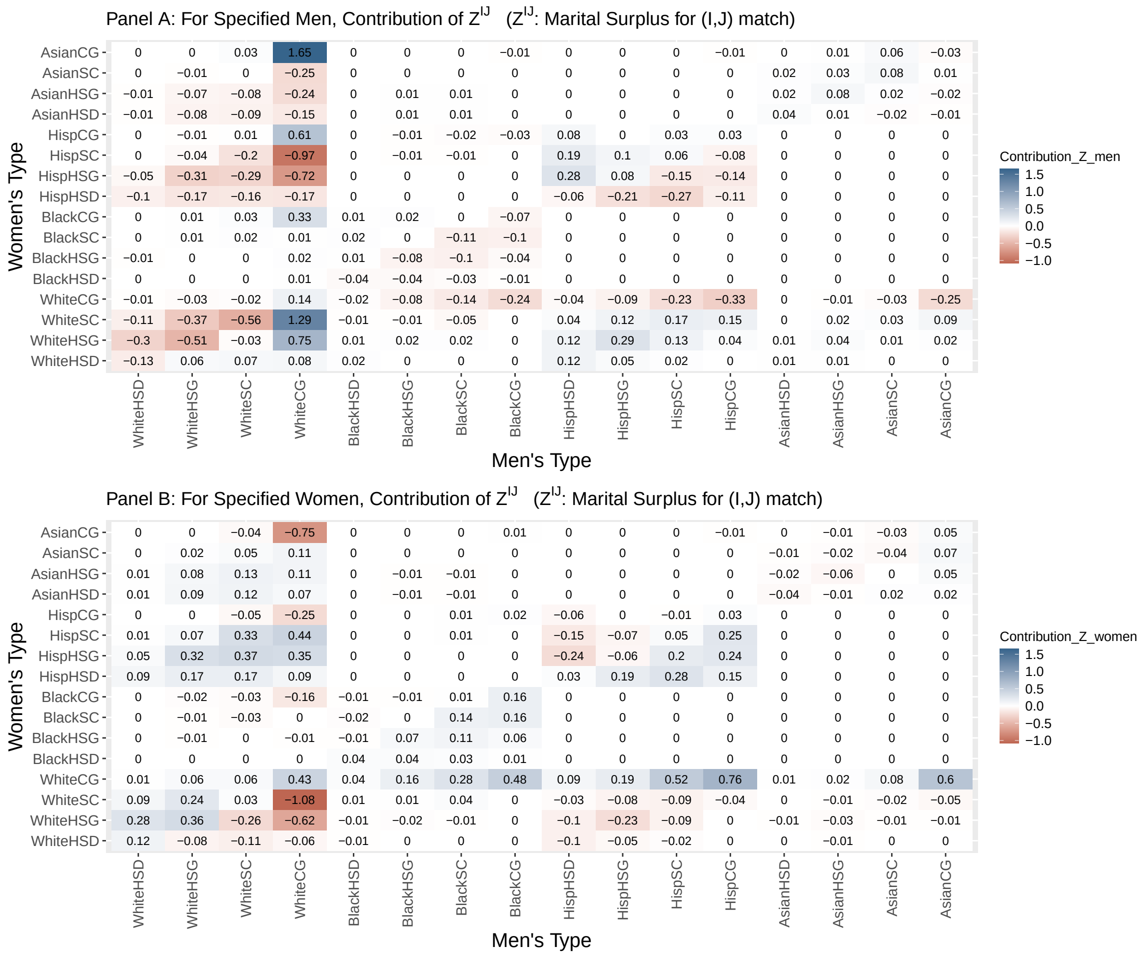
Note: Panel A presents the decomposition results for white CG men's changes in the welfare gains from marital desegregation over time. Specifically, Panel A only presents the decomposition results regarding female population model primitives. Panel B presents the decomposition results for white CG women's changes in the welfare gains from marital desegregationover time. Specifically, Panel A only presents the decomposition results regarding male population model primitives.

Figure A.6: Contribution of Each Marital Surplus Primitive to the 1980-2019 Change in the Welfare Gains, For White CG Women and White HSG Women



Note: Panel A presents the decomposition results for White CG women's changes in the welfare gains from marital desegregation over time. Panel B presents the decomposition results for White HSG women's changes in the welfare gains from marital desegregation over time. Only the contributions made by marital surplus are presented.

Figure A.7: Contribution of Each Marital Surplus Primitive to the 1980-2019 Change in the Welfare Gains, For White CG



Note: Panel A presents the decomposition results for White CG men's changes in the welfare gains from marital desegregation over time. Panel B presents the decomposition results for White CG women's changes in the welfare gains from marital desegregation over time. Only the contributions made by marital surplus are presented.

Appendix B: Appendix to Chapter 2

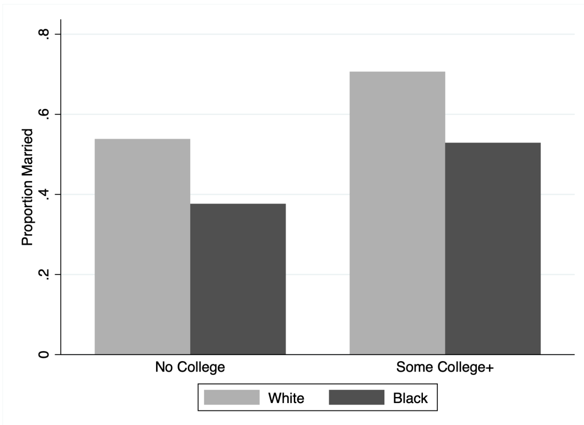
B.1 Additional Tables

Table B.1: Definition of Census Regions

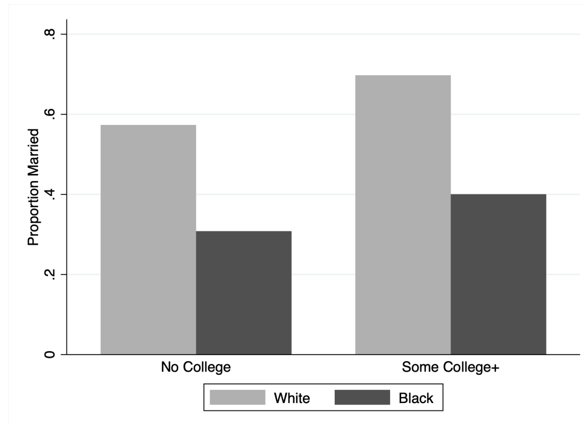
Region	List of States
New England	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont
Middle Atlantic	New Jersey, New York, Pennsylvania
East North Central	Illinois, Indiana, Michigan, Ohio, Wisconsin
West North Central	Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota
South Atlantic	Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, Washington D.C., West Virginia
East South Central	Alabama, Kentucky, Mississippi, Tennessee
West South Central	Arkansas, Louisiana, Oklahoma, Texas
Mountain	Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming
Pacific	Alaska, California, Hawaii, Oregon, Washington

B.2 Additional Figures

Figure B.1: Marriage Rate by Race and Gender, 2019



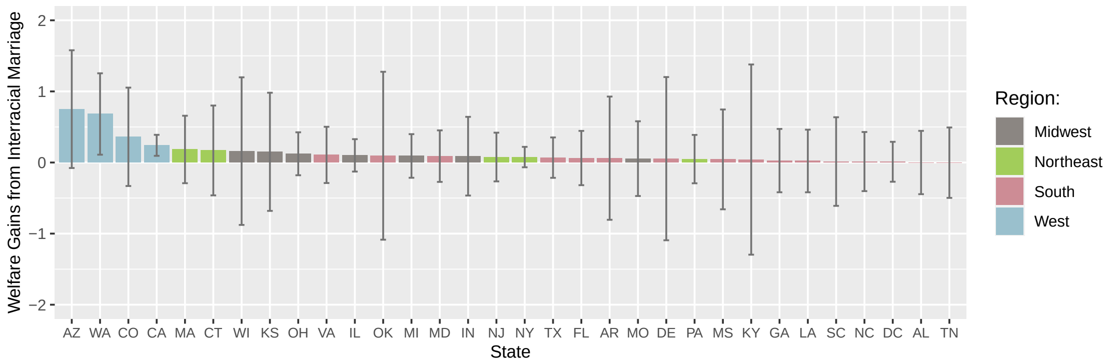
(a) Among Men



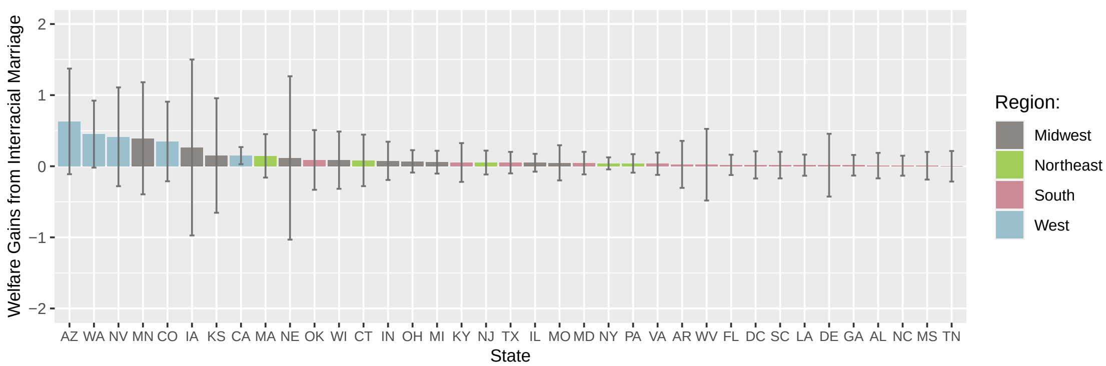
(b) Among Women

Note: This figure shows the proportion of married people among the specified group aged 35-50. Data source is 2019 5% sample American Community Survey (2015-2019 5 year pooled sample). Survey weight is applied.

Figure B.2: Welfare Gains from Interracial Marriage, Black Men, 1980



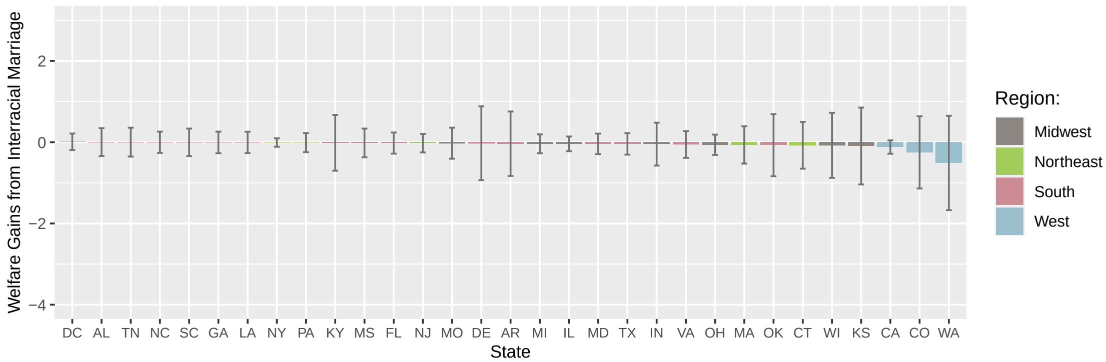
(a) Some College+ Black Men



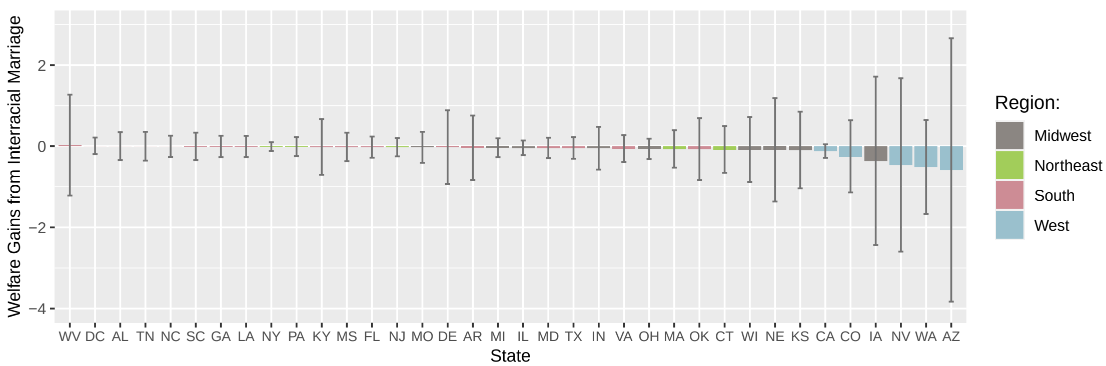
(b) No College Black Men

Note: These figures plot the welfare gain from marital desegregation following the approach in Koh, 2022 for each specified type of men in each state. Data used to calculate the gains are 1980 Decennial Census. Further details on the sample restriction are described in Section 2.2.1. Shade for each line refers to the 95% confidence interval. Standard errors are calculated from the sampling variation in the data.

Figure B.3: Welfare Gains from Interracial Marriage, Black Women, 1980



(a) Some College+ Black Women



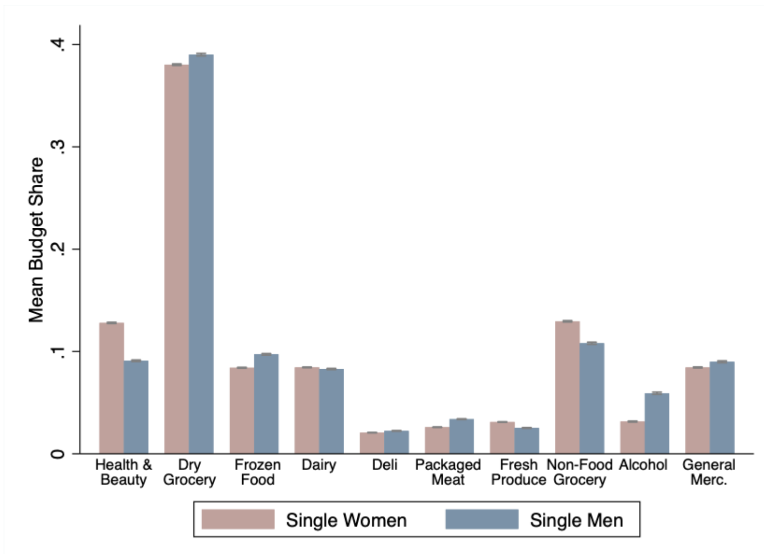
(b) No College Black Women

Note: These figures plot the welfare gain from marital desegregation following the approach in Koh, 2022 for each specified type of women in each state. Data used to calculate the gains are 1980 Decennial Census. Further details on the sample restriction are described in Section 2.2.1. Shade for each line refers to the 95% confidence interval. Standard errors are calculated from the sampling variation in the data.

Appendix C: Appendix to Chapter 3

C.1 Additional Figures

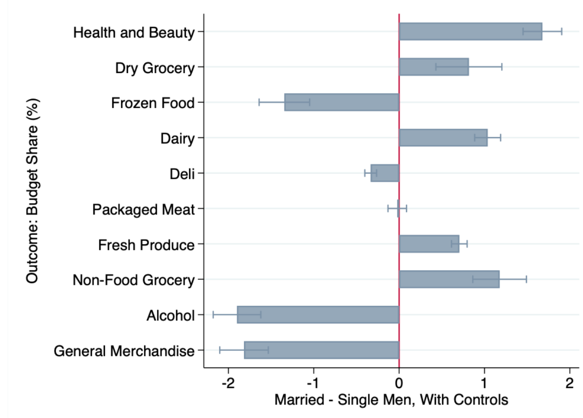
Figure C.1: Mean Budget Shares by Gender, Singles Living Alone



Note: Consumer panel 2004-2017. Sample is limited to single men and women living alone and whose age is between 25-64. This plot shows the mean budget share for each consumption categories. 95% confidence intervals are indicated by the error bars.

Figure C.2: Singles vs. Couples

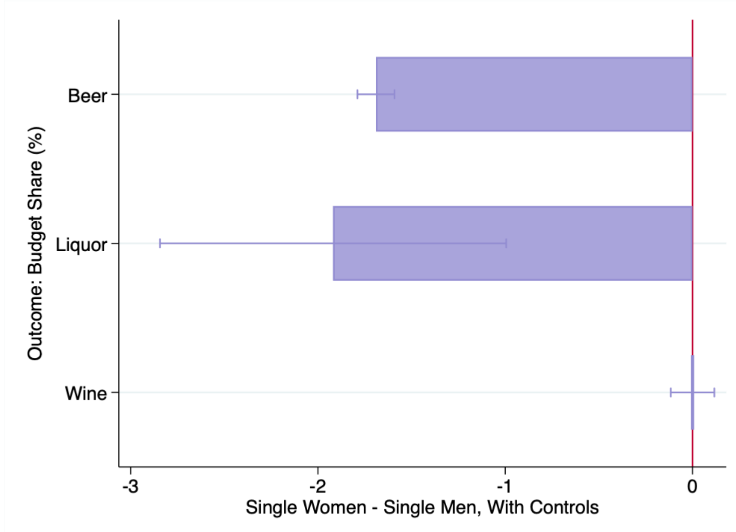
(a) Single Women vs. Couples



(b) Single Men vs. Couples

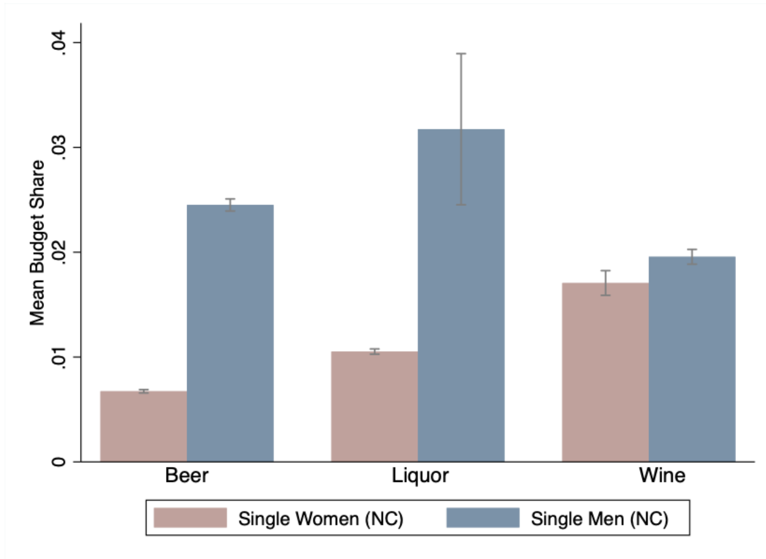
Note: Consumer Panel 2004-2017. Panel (a) includes single women living alone and between age 25-64 and couples without children and both spouses between age 25-64. Panel (b) includes single men living alone and under age 65 and couples without children and both spouses between age 25-64. This figure shows the result from regression of budget share for corresponding aggregate good (y-axis) on married couple indicator and various controls. The bar indicates the regression coefficient on the married couple indicator. Control variables included in the regressions are: household head's age, household head's years of education, household head's unemployment status, household income, dummies for Black and Hispanic, year fixed effects, county fixed effects. For married couple, household head is defined to be male head. Household weights are applied. Standard errors are clustered at the county level.

Figure C.3: Consumption Patterns by Single Women vs Single Men without Children, Detailed Alcohol



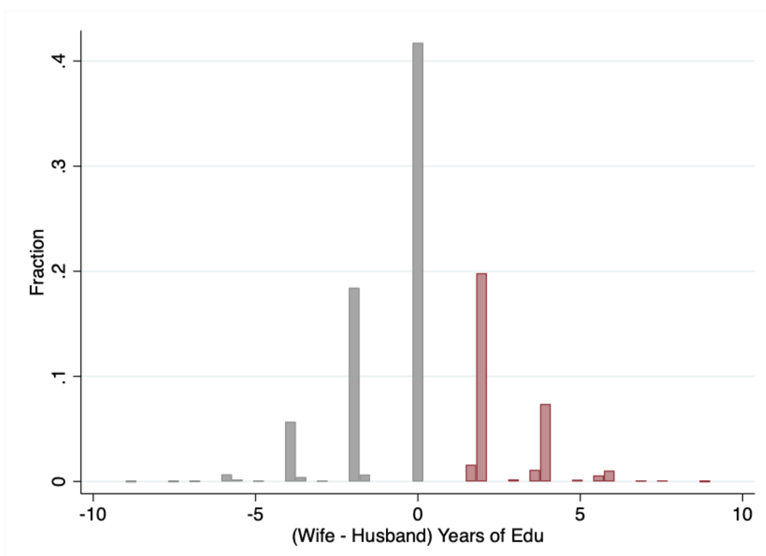
Note: Consumer Panel 2004-2017. Sample only includes singles between age 25-64 without children. This figure shows the result from regression of budget share for corresponding aggregate good (y-axis) on female indicator and various controls. The bar indicates the regression coefficient on the female indicator. Control variables included in the regressions are: age, years of education, unemployment status, household income, dummies for Black and Hispanic, year fixed effects, county fixed effects. Household weights are applied. Standard errors are clustered at the county level.

Figure C.4: Raw Budget Share by Gender, Single Without Child



Note: Consumer panel 2004-2017. Sample is limited to single men and women without child and who are between age 25-64. This plot shows the mean budget share for each consumption categories. 95% confidence intervals are indicated by the error bars.

Figure C.5: Distribution of (Wife - Husband) Years of Education



Note: Consumer Panel 2004-2017. Sample only includes couples with both spouses aged between 25-64.

C.2 Additional Tables

C.2.1 Descriptive

Table C.1: Description of Nielsen Departments

Department	**Description**
Health and Beauty Aids	e.g. baby care, cosmetics, cough & cold remedies, deodorant, hair care, oral hygiene, pain remedies, skin care, fragrances, shaving
Dry Grocery	e.g. baking mixes, bottle water, candy, carbonated beverages, cereal, coffee, condiments, crackers, pet food, prepared foods, snacks, soup, canned vegetables
Frozen Food	e.g. ice cream, frozen pizza, frozen vegetables
Dairy	e.g. cheese, eggs, yogurt
Deli	
Packaged Meat	
Fresh Produce	
Non-Food Grocery	e.g. detergent, diapers, fresheners/deodorizers, household cleaners, laundry supplies, pet care
Alcohol	e.g. beer, wine, liquor, coolers
General Merchandise	e.g. batteries/flashlights, candles, computer/electronic, cookware, film/cameras, insecticides, lawn & garden, motor vehicle, office supplies

Table C.2: Demographic Characteristics of Married Couples

	(1) Married
Household Income	69633.25 (31102.8)
Household Size	3.13 (1.262)
Black	0.08 (0.265)
Hispanic	0.08 (0.268)
Age, Female Head	48.03 (9.777)
Years of Education, Female Head	14.58 (2.012)
Unemployed, Female Head	0.33 (0.471)
Age, Male Head	49.73 (9.553)
Years of Education, Male Head	14.39 (2.142)
Unemployed, Male Head	0.15 (0.360)
Observations	327957

Note: Nielsen Consumer Panel 2004-2017. Sample is limited to couples where both female and male heads are between age 25-64. Dollars are inflation-adjusted and are based on 2010 USD. Standard deviations are in parentheses.

Table C.3: Industry Composition by Gender (%)

	Men	Women
Manufacturing	17.67	9.53
Construction	12.07	1.49
Retail Trade	10.58	12.57
Transporation and Warehousing	6.03	2.39
Accommodation and Food Services	6.02	8.18
Public Administration	5.68	4.51
Professional, Scientific, and Technical Services	5.51	5.50
Educational Services	4.72	11.97
Wholesale Trade	4.62	2.36
Other Services (except Public Administration)	4.49	5.11
Health Care and Social Assistance	4.23	18.56
Administrative and Support and Waste Management and Remediation Services	4.02	3.50
Finance and Insurance	3.39	6.36
Information	3.06	2.94
Agriculture, Forestry, Fishing and Hunting	2.23	0.72
Arts, Entertainment, and Recreation	1.98	1.85
Real Estate and Rental and Leasing	1.71	1.84
Utilities	1.30	0.43
Mining, Quarrying, and Oil and Gas Extraction	0.65	0.11
Management of Companies and Enterprises	0.04	0.06
Total	100.00	100.00

Note: Share of men and women in each industry is calculated using employed samples in census 2000. We follow 2-digit NAICS industry classifications. They are weighted by census population weights.

C.2.2 Main Results: Relative Education

Table C.4: Effect of (Wife-Husband) Years of Education Conditional on Husband's Education on Budget Share (%), (Aggregate I)

	(1) Health Care b/se	(2) Beauty b/se	(3) Other Health b/se	(4) All Food b/se	(5) Alcohol b/se	(6) Tobacco and Accessories b/se
(Wife - Husband) Edu	0.0919***	0.0321***	0.0199***	0.0066	-0.0553***	-0.1711***
	(0.0109)	(0.0081)	(0.0024)	(0.0309)	(0.0170)	(0.0131)
Years of Education, Male Head	0.1938***	0.0280***	0.0257***	-0.1183***	0.0082	-0.3240***
	(0.0136)	(0.0096)	(0.0027)	(0.0387)	(0.0206)	(0.0163)
Observations	333834	333834	333834	333834	333834	333834
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Budget Share (%)	5.895	3.465	0.382	67.80	2.827	1.476
R-squared	0.103	0.0808	0.0745	0.138	0.112	0.128

Note: 2004-2017 Consumer Panel. Sample is limited to couples where both husband and wife are aged 25-64. Controls include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, and occupation fixed effects for male and female heads. County fixed effects and year fixed effects are included. Household weights are applied. Standard errors are clustered at the county level. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level..

Table C.5: Effect of (Wife-Husband) Years of Education on Budget Share (%), (Aggregate I)

	(1) Health Care b/se	(2) Beauty b/se	(3) Other Health b/se	(4) All Food b/se	(5) Alcohol b/se	(6) Tobacco and Accessories b/se
(Wife - Husband) Edu	-0.0071	0.0178***	0.0068***	0.0670***	-0.0595***	-0.0057
	(0.0088)	(0.0063)	(0.0020)	(0.0250)	(0.0130)	(0.0103)
Observations	333834	333834	333834	333834	333834	333834
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Budget Share (%)	5.895	3.465	0.382	67.80	2.827	1.476
R-squared	0.0987	0.0806	0.0733	0.138	0.112	0.121

Note: 2004-2017 Consumer Panel. Sample is limited to couples where both husband and wife are aged 25-64. Controls include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, and occupation fixed effects for male and female heads. County fixed effects and year fixed effects are included. Household weights are applied. Standard errors are clustered at the county level. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

Table C.6: Effect of (Wife-Husband) Years of Education Conditional on Husband's Education on Budget Share (%), (Aggregate II)

	(1) Non-Food Grocery b/se	(2) Automo/Batteries/Electron/Hardware b/se	(3) Book/Stationary/SchoolSup b/se	(4) Kitchen/Houseware/Garden b/se	(5) Photo/Toys/Sports b/se	(6) Other Supplies b/se
(Wife - Husband) Edu	0.0251**	0.0033	0.0379***	0.0037	0.0060**	-0.0000
	(0.0125)	(0.0078)	(0.0038)	(0.0066)	(0.0028)	(0.0001)
Years of Education, Male Head	0.0187	0.0489***	0.0559***	0.0450***	0.0180***	0.0001
	(0.0158)	(0.0090)	(0.0043)	(0.0079)	(0.0031)	(0.0001)
Observations	333834	333834	333834	333834	333834	333834
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Budget Share (%)	10.80	2.670	1.251	3.147	0.279	0.00852
R-squared	0.101	0.0951	0.0524	0.0680	0.0411	0.0365

Note: 2004-2017 Consumer Panel. Sample is limited to couples where both husband and wife are aged 25-64. Controls include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, and occupation fixed effects for male and female heads. County fixed effects and year fixed effects are included. Household weights are applied. Standard errors are clustered at the county level. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level..

Table C.7: Effect of (Wife-Husband) Years of Education on Budget Share (%), (Aggregate II)

	(1) Non-Food Grocery b/se	(2) Automo/Batteries/Electron/Hardware b/se	(3) Book/Stationary/SchoolSup b/se	(4) Kitchen/Houseware/Garden b/se	(5) Photo/Toys/Sports b/se	(6) Other Supplies b/se
(Wife - Husband) Edu	0.0155	-0.0216***	0.0093***	-0.0192***	-0.0032	-0.0001
	(0.0101)	(0.0065)	(0.0031)	(0.0050)	(0.0022)	(0.0001)
Observations	333834	333834	333834	333834	333834	333834
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Budget Share (%)	10.80	2.670	1.251	3.147	0.279	0.00852
R-squared	0.101	0.0946	0.0505	0.0675	0.0408	0.0365

Note: 2004-2017 Consumer Panel. Sample is limited to couples where both husband and wife are aged 25-64. Controls include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, and occupation fixed effects for male and female heads. County fixed effects and year fixed effects are included. Household weights are applied. Standard errors are clustered at the county level. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

C.2.3 Main Results: Relative Potential Wages

Table C.8: Effect of Gender Wage Ratio on Budget Share (%), (Aggregate I)

	(1) Health Care b/se	(2) Beauty b/se	(3) Other Health b/se	(4) All Food b/se	(5) Alcohol b/se	(6) Tobacco and Accessories b/se
(Female Wage)/(Male Wage)	-0.0699	0.6609***	-0.1111*	0.1909	-0.5555*	-0.1080
	(0.2718)	(0.1921)	(0.0587)	(0.7159)	(0.3315)	(0.2666)
Observations	332403	332403	332403	332403	332403	332403
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Budget Share (%)	5.895	3.466	0.382	67.81	2.830	1.472
R-squared	0.122	0.0941	0.0912	0.159	0.131	0.157

Note: 2004-2017 Consumer Panel. Sample is limited to couples where both husband and wife are aged 25-64. Controls include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, years of education of male and female heads, and occupation fixed effects for male and female heads. County fixed effects and year fixed effects are included. Household weights are applied. Standard errors are clustered at the county level. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

Table C.9: Effect of Respective Gender Wage on Budget Share (%), (Aggregate I)

	(1) Health Care b/se	(2) Beauty b/se	(3) Other Health b/se	(4) All Food b/se	(5) Alcohol b/se	(6) Tobacco and Accessories b/se
Female Wage (1,000 USD)	-0.0115	0.0116	-0.0037*	0.0190	-0.0168	0.0072
	(0.0113)	(0.0075)	(0.0022)	(0.0280)	(0.0143)	(0.0115)
Male Wage (1,000 USD)	-0.0034	-0.0187***	0.0012	0.0018	0.0175*	0.0091
	(0.0077)	(0.0056)	(0.0019)	(0.0247)	(0.0103)	(0.0086)
Observations	332403	332403	332403	332403	332403	332403
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Budget Share (%)	5.895	3.466	0.382	67.81	2.830	1.472
R-squared	0.123	0.0941	0.0912	0.159	0.131	0.158

Note: 2004-2017 Consumer Panel. Sample is limited to couples where both husband and wife are aged 25-64. Controls include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, years of education of male and female heads, and occupation fixed effects for male and female heads. County fixed effects and year fixed effects are included. Household weights are applied. Standard errors are clustered at the county level. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

Table C.10: Effect of Gender Wage Ratio on Budget Share (%) (Aggregate II)

	(1) Non-Food Grocery b/se	(2) Automo/Batteries/Electron/Hardware b/se	(3) Book/Stationary/SchoolSup b/se	(4) Kitchen/Houseware/Garden b/se	(5) Photo/Toys/Sports b/se	(6) Other Supplies b/se
(Female Wage)/(Male Wage)	-0.4698*	0.2230	0.2070**	0.0723	-0.0407	0.0010
	(0.2731)	(0.2116)	(0.0984)	(0.1604)	(0.0613)	(0.0030)
Observations	332403	332403	332403	332403	332403	332403
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Budget Share (%)	10.79	2.668	1.252	3.144	0.279	0.00852
R-squared	0.123	0.112	0.0794	0.0881	0.0577	0.0520

Note: 2004-2017 Consumer Panel. Sample is limited to couples where both husband and wife are aged 25-64. Controls include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, years of education of male and female heads, and occupation fixed effects for male and female heads. County fixed effects and year fixed effects are included. Household weights are applied. Standard errors are clustered at the county level. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

Table C.11: Effect of Respective Gender Wage on Budget Share (%) (Aggregate II)

	(1) Non-Food Grocery b/se	(2) Automo/Batteries/Electron/Hardware b/se	(3) Book/Stationary/SchoolSup b/se	(4) Kitchen/Houseware/Garden b/se	(5) Photo/Toys/Sports b/se	(6) Other Supplies b/se
Female Wage (1,000 USD)	-0.0188	0.0083	0.0069*	-0.0007	-0.0018	0.0003**
	(0.0120)	(0.0065)	(0.0036)	(0.0065)	(0.0026)	(0.0001)
Male Wage (1,000 USD)	0.0037	-0.0023	-0.0051*	-0.0047	0.0008	0.0001
	(0.0086)	(0.0068)	(0.0029)	(0.0058)	(0.0020)	(0.0001)
Observations	332403	332403	332403	332403	332403	332403
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Budget Share (%)	10.79	2.668	1.252	3.144	0.279	0.00852
R-squared	0.123	0.112	0.0794	0.0882	0.0577	0.0521

Note: 2004-2017 Consumer Panel. Sample is limited to couples where both husband and wife are aged 25-64. Controls include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, years of education of male and female heads, and occupation fixed effects for male and female heads. County fixed effects and year fixed effects are included. Household weights are applied. Standard errors are clustered at the county level. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

Table C.12: Effect of Gender Wage Ratio on Food Budget Share (%)

	(1) Dry Grocery b/se	(2) Frozen Food b/se	(3) Dairy b/se	(4) Deli b/se	(5) Packaged Meat b/se	(6) Fresh Produce b/se
(Female Wage)/(Male Wage)	-0.1528	0.4453	-0.0091	0.0926	-0.1025	-0.2734
	(0.5236)	(0.3314)	(0.3786)	(0.1345)	(0.1972)	(0.2775)
Observations	332395	332395	332395	332395	332395	332395
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Budget Share (%)	59.77	12.93	14.37	3.042	5.365	4.517
R-squared	0.135	0.109	0.174	0.0991	0.195	0.158

Note: 2004-2017 Consumer Panel. Sample is limited to couples where both husband and wife are aged 25-64. Controls include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, years of education of male and female heads, and occupation fixed effects for male and female heads. County fixed effects and year fixed effects are included. Household weights are applied.Standard errors are clustered at the county level. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

Table C.13: Effect of Wage by Gender on Food Budget Share (%)

	(1) Dry Grocery b/se	(2) Frozen Food b/se	(3) Dairy b/se	(4) Deli b/se	(5) Packaged Meat b/se	(6) Fresh Produce b/se
Female Wage (1,000 USD)	-0.0142	0.0121	-0.0024	0.0108*	0.0033	-0.0096
	(0.0217)	(0.0133)	(0.0136)	(0.0057)	(0.0072)	(0.0101)
Male Wage (1,000 USD)	-0.0078	-0.0084	-0.0018	0.0044	0.0036	0.0100
	(0.0152)	(0.0099)	(0.0124)	(0.0040)	(0.0063)	(0.0086)
Observations	332395	332395	332395	332395	332395	332395
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Budget Share (%)	59.77	12.93	14.37	3.042	5.365	4.517
R-squared	0.135	0.109	0.174	0.0992	0.195	0.158

Note: 2004-2017 Consumer Panel. Sample is limited to couples where both husband and wife are aged 25-64. Controls include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, years of education of male and female heads, and occupation fixed effects for male and female heads. County fixed effects and year fixed effects are included. Household weights are applied. Standard errors are clustered at the county level. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

Table C.14: Effect of Gender Wage Ratio on Detailed Health and Beauty (%)

	(1) Baby Needs b/se	(2) Women's Beauty b/se	(3) Health b/se	(4) Hygiene b/se	(5) Shaving, Cleansing, Hair Care b/se	(6) Men's Beauty b/se	(7) Health Supplements b/se
(Female Wage)/(Male Wage)	-0.0917	0.3733***	0.0053	0.1173	0.2942***	-0.0337**	-0.0630
	(0.0563)	(0.0993)	(0.1997)	(0.0755)	(0.1070)	(0.0156)	(0.1531)
Observations	332412	332412	332412	332412	332412	332412	332412
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Budget Share (%)	0.318	1.146	3.479	1.688	1.894	0.0857	1.651
R-squared	0.0989	0.0824	0.128	0.103	0.0911	0.0671	0.101

Note: 2004-2017 Consumer Panel. Sample is limited to couples where both husband and wife are aged 25-64. Controls include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, years of education of male and female heads, and occupation fixed effects for male and female heads. County fixed effects and year fixed effects are included. Household weights are applied. Standard errors are clustered at the county level. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

Table C.15: Effect of Wage by Gender on Detailed Health and Beauty (%)

	(1) Baby Needs b/se	(2) Women's Beauty b/se	(3) Health b/se	(4) Hygiene b/se	(5) Shaving, Cleansing, Hair Care b/se	(6) Men's Beauty b/se	(7) Health Supplements b/se
Female Wage (1,000 USD)	-0.0024	0.0113***	-0.0032	-0.0023	0.0019	-0.0022**	-0.0062
	(0.0020)	(0.0031)	(0.0080)	(0.0031)	(0.0044)	(0.0010)	(0.0061)
Male Wage (1,000 USD)	0.0012	-0.0065**	-0.0008	-0.0060***	-0.0094***	-0.0003	-0.0005
	(0.0017)	(0.0026)	(0.0054)	(0.0023)	(0.0030)	(0.0006)	(0.0039)
Observations	332412	332412	332412	332412	332412	332412	332412
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Budget Share (%)	0.318	1.146	3.479	1.688	1.894	0.0857	1.651
R-squared	0.0989	0.0824	0.128	0.104	0.0911	0.0673	0.101

Note: 2004-2017 Consumer Panel. Sample is limited to couples where both husband and wife are aged 25-64. Controls include: household total expenditure, Black, Hispanic, household size, number of children, ages of female and male heads, years of education of male and female heads, and occupation fixed effects for male and female heads. County fixed effects and year fixed effects are included. Household weights are applied. Standard errors are clustered at the county level. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

C.2.4 Additional Results

Table C.16: Effect of Respective Gender Wage on Budget Share (%), Singles Living Alone

	(1) Health Care	(2) Beauty	(3) Other Health	(4) All Food	(5) Alcohol	(6) Tobacco and Accessories
Panel A: Single Female Living Alone						
(Female Wage)/(Male Wage)	0.584	2.034*	-0.068	1.293	-0.845	-1.594
	(1.786)	(1.129)	(0.101)	(3.220)	(1.206)	(1.717)
Budget Share Mean (%)	8.302	4.342	0.170	62.550	3.159	2.541
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82267	82267	82267	82267	82267	82267
Panel B: Single Male Living Alone						
(Female Wage)/(Male Wage)	-0.413	-0.145	0.064	-3.737	-4.243	0.673
	(2.046)	(1.589)	(0.137)	(6.552)	(3.507)	(3.553)
Budget Share Mean (%)	6.845	2.109	0.163	65.091	5.938	3.209
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41401	41401	41401	41401	41401	41401

Note: 2004-2017 Consumer Panel. In Panel A, the sample is limited to single females aged 25-64 living alone. In Panel B, the sample is limited to single males aged 25-64 living alone. Control variables include: total expenditure, dummies for Black and Hispanic, age, years of education, occupation categories. County fixed effects and year fixed effects are included. Household weights are applied. Standard errors are clustered at the county level. *** Significant at 1% level, **: Significant at 5% level, *: Significant at 10% level.

C.2.5 Summary of Rotemberg Weight

Table C.17: Summary of Rotemberg Weight for Female Potential Wage

Panel A: Women's Beauty Budget Share				
I. Negative and positive weights				
	Sum	Mean	Share	
Negative	-0.106	-0.035	0.087	
Positive	1.106	0.065	0.913	
II. Top 5 Rotemberg weight industries				
	$\hat{\alpha}_k$	$\hat{\beta}_k$	95 % CI	Ind Share
Accomm. and Food Services	0.342	0.008	[-.003, .018]	7.315
Finance and Insurance	0.205	0.013	[-.003, .031]	6.738
Retail Trade	0.188	0.016	[.002, .031]	12.144
Professional, Scientific, Technical	0.125	0.010	[-.001, .021]	5.637
Other Services	0.076	0.000	[-.018, .022]	4.957
Panel B: Beer Budget Share				
I. Negative and positive weights				
	Sum	Mean	Share	
Negative	-0.106	-0.035	0.087	
Positive	1.106	0.065	0.913	
II. Top 5 Rotemberg weight industries				
	$\hat{\alpha}_k$	$\hat{\beta}_k$	95 % CI	Ind Share
Accomm. and Food Services	0.342	-0.007	[-.034, .018]	7.315
Finance and Insurance	0.205	-0.027	[-.057, 0]	6.738
Retail Trade	0.188	-0.017	[-.048, .014]	12.144
Professional, Scientific, Technical	0.125	-0.013	[-.04, .021]	5.637
Other Services	0.076	0.017	[-.016, .046]	4.957

Note: This table reports statistics about the Rotemberg weights for female industry shares. Sample used to generate this table is couples where both husband and wife are aged 25-64 in 2004-2017 Consumer Panel. Panel A uses "Women's Beauty Budget Share" as outcome variable, and Panel B uses "Beer Budget Share" as outcome variable. Following Goldsmith-Pinkham, Sorkin, and Swift, 2020, we report the aggregated weights, where we aggregate a given industry across years. Part I. for each panel reports the share and sum of negative weights. Part II. for each panel reports the top five industries according to the Rotemberg weights (α_k). $\hat{\beta}_k$ is the coefficient from the just-identified regression, and the 95% confidence interval is the weak instrument robust confidence interval using the method from Chernozkukhov and Hansen, 2008. Ind Share is the industry share.

Table C.18: Summary of Rotemberg Weight for Male Potential Wage

Panel A: Women's Beauty Budget Share				
I. Negative and positive weights				
	Sum	Mean	Share	
Negative	-0.046	-0.023	0.042	
Positive	1.046	0.058	0.958	
II. Top 5 Rotemberg weight industries				
	$\hat{\alpha}_k$	$\hat{\beta}_k$	95 % CI	Ind Share
Finance and Insurance	0.249	-0.007	[-.011, -.003]	3.336
Accomm. and Food Services	0.194	-0.016	[-.029, -.004]	5.479
Professional, Scientific, Technical	0.171	-0.004	[-.012, .004]	5.442
Retail Trade	0.108	-0.010	[-.02, 0]	10.660
Information	0.068	-0.018	[-.028, -.009]	3.063
Panel B: Alcohol Budget Share				
I. Negative and positive weights				
	Sum	Mean	Share	
Negative	-0.046	-0.023	0.042	
Positive	1.046	0.058	0.958	
II. Top 5 Rotemberg weight industries				
	$\hat{\alpha}_k$	$\hat{\beta}_k$	95 % CI	Ind Share
Finance and Insurance	0.249	0.015	[-.024, .043]	3.336
Accomm. and Food Services	0.194	0.037	[.01, .064]	5.479
Professional, Scientific, Technical	0.171	0.024	[-.002, .053]	5.442
Retail Trade	0.108	0.019	[-.02, .055]	10.660
Information	0.068	0.017	[-.004, .038]	3.063

Note: This table reports statistics about the Rotemberg weights for male industry shares. Sample used to generate this table is couples where both husband and wife are aged 25-64 in 2004-2017 Consumer Panel. Panel A uses "Women's Beauty Budget Share" as outcome variable, and Panel B uses "Alcohol Budget Share" as outcome variable. Following Goldsmith-Pinkham, Sorkin, and Swift, 2020, we report the aggregated weights, where we aggregate a given industry across years. Part I. for each panel reports the share and sum of negative weights. Part II. for each panel reports the top five industries according to the Rotemberg weights (α_k). $\hat{\beta}_k$ is the coefficient from the just-identified regression, and the 95% confidence interval is the weak instrument robust confidence interval using the method from Chernozkukhov and Hansen, 2008. Ind Share is the industry share.

C.3 Calculating the Rotemberg Weights

Following the general approach of the literature on gender-relative potential wage (Aizer, 2010; Bertrand, Kamenica, and Pan, 2015; Shenhav, 2021), we use the Bartik-style potential wage for each gender as a reduced form measure rather than as an instrument for observed gender wage, which we do not observe in our data. Therefore, we estimate reduced form Bartik Rotemberg weights following the approach outlined in Goldsmith-Pinkham, Sorkin, and Swift, 2020. We describe the estimation procedure below.

As introduced in Section 3.6.1, our Bartik measure for female potential wage is $\bar{w}_{female,recy} = \sum_j \gamma_{female,recj} w_{-cyj}$, and male potential wage is $\bar{w}_{male,recy} = \sum_j \gamma_{male,recj} w_{-cyj}$. We will calculate the Rotemberg weight for each industry share for each gender separately using Equation 3.3, which is one of our main estimation equations. For clarity, we will simplify notations here to describe how we calculate the Rotemberg weight for each gender's potential wage. Let's consider the case for female potential wage. Let us rewrite the Equation 3.3 as the following:

$$Y_{hy} = \beta_f B_{hy} + \mathbf{W}_{hy}\gamma + \varepsilon_{hy}$$

where Y_{hy} is the budget share of the specified aggregate good for household h in year y, B_{hy} is the female potential wage matched to wife's race r, education e_w, county c and year y, and $\mathbf{W}_{hy}$ are the controls, which include a constant, male potential wage, and all demographic controls and fixed effects as specified in Equation 3.3.

Goldsmith-Pinkham, Sorkin, and Swift, 2020 have shown that the estimate for β_f can be written as:

$$\hat{\beta}_f = (B'B^{\perp})^{-1}(B'Y^{\perp})$$

where $B^{\perp}$ are residuals from regressing B_{hy} on $\mathbf{W}_{hy}$ and $Y^{\perp}$ are the residuals from regressing Y_{hy}

on $\mathbf{W}_{hy}$. They show that as a result, it is possible to rewrite this as:

$$\hat{\beta}_f = \sum_k \hat{\alpha}_k \hat{\beta}_k, \quad \hat{\beta}_k = (\gamma_k^{female'} B^{\perp})^{-1} (\gamma_k^{female'} Y^{\perp})$$

where γ_k^{female} is the female industry share in 2000 for industry k for education level e, race r, county c, which is matched to each household. This shows that each β_k can be recovered by using the industry share for industry k as an instrument for the reduced form Bartik measure of female potential wage.

The Rotemberg weight for each industry k is expressed as the following:

$$\hat{\alpha}_k = \frac{w_k \gamma_k^{female'} B^{\perp}}{\sum_{k'} w_{k'} \gamma_{k'}^{female'} B^{\perp}}$$

where w_k is the wage of industry k in each state in year y. Rotemberg weights for male potential wage are estimated using a similar procedure as above, using different $\mathbf{W}_{hy}$ that now include female potential wage instead of male potential wage.