Gender identity and relative income within households

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Abstract

We examine causes and consequences of relative income within households. We establish that gender identity – in particular, an aversion to the wife earning more than the husband - impacts marriage formation, the wife's labor force participation, the wife's income conditional on working, marriage satisfaction, likelihood of divorce, and the division of home production. The distribution of the share of household income earned by the wife exhibits a sharp cliff at 0.5, which suggests that a couple is less willing to match if her income exceeds his. Within marriage markets, when a randomly chosen woman becomes more likely to earn more than a randomly chosen man, marriage rates decline. Within couples, if the wife's potential income (based on her demographics) is likely to exceed the husband's, the wife is less likely to be in the labor force and earns less than her potential if she does work. Couples where the wife earns more than the husband are less satisfied with their marriage and are more likely to divorce. Finally, based on time use surveys, the gender gap in non-market work is larger if the wife earns more than the husband.

Keywords: gender roles; gender gap; marriage market
JEL: D10; J12; J16

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1 Introduction

Women have experienced substantial labor market gains over the last half century. The gender gap in labor force participation and the gender gap in earnings have both declined. Several factors have been identified as contributing to these gains. First and foremost has been the reduction in the gender gap in education (Blau and Kahn 2006). Various technological innovations, such as the contraceptive pill, have favored women (Goldin and Katz 2002, Greenwood *et al.* 2005). Labor demand has shifted towards industries where female skills are disproportionally represented (Weinberg 2000, Black and Juhn 2000). Finally, better regulatory controls and greater competitiveness have reduced labor market discrimination against women (Black and Strahan 2001, Black and Brainerd 2004).

Despite these gains, and despite the fact that women have now overtaken men in terms of educational achievement (Goldin *et al.* 2006), substantial gender gaps remain, both in labor force participation and in earnings. Female labor force participation appears to have plateaued since the early to mid-1990s (Blau and Kahn 2006) and about a 25 percent gender gap in earnings remains among full-time-full-year workers.

This halted progress has led researchers to consider less traditional (within economics at least) factors that might influence the gender gap in labor market outcomes (Bertrand 2010). One explanation that has gained popularity over the last decade is that slow-moving identity norms shape behavior. Influential work by Akerlof and Kranton (2000, 2010) imports insights about identity from sociology and social psychology into economics. Akerlof and Kranton (2000) define identity as one's sense of belonging to a social category, coupled with a view about how people who belong to that category should behave. They propose that identity influences economic outcomes because deviating from the prescribed behavior is inherently costly. In one application of this model, the two relevant social categories are *man* and *woman*, and these two categories are associated with specific behavioral prescriptions, such as "men work in the labor force and women work in the home" and "a man should earn more than his wife." If deviating from these prescriptions is costly, gender identity would lead to lower labor force participation and lower earnings for women.

Does gender identity indeed impact the gender gap in labor market outcomes? Does it influence other outcomes, such as marriage formation and division of household chores? In this paper, we examine these questions, focusing on the behavioral prescription that "a man should earn more than his wife."

We first examine the distribution of the share of the household labor income earned by the wife. Using 2008-2010 American Community Survey data on young couples, Panel (a) of Figure 1 (in Section 2) shows that this distribution exhibits a sharp drop to the right of 0.5 – when the wife starts to earn more than the husband.[1] This drop suggests that gender identity plays an important role in marriage formation. The other two panels of Figure 1 show the counterfactual distributions that would arise if matches were formed through costly search within marriage markets defined by age, race, and education.[2] The outcome in Panel (b) stems from the assumption that both men and women prefer partners with higher income. Panel (c) depicts the distribution that would arise if men dislike women's income once it exceeds their own. Only the distribution generated by the gender identity norms (Panel (c)) shares the key distinctive feature of the true distribution – the sharp drop at 0.5.

We next turn from the analysis of who marries whom to the analysis of whether people get married at all. Using 1970 to 2010 data from the US Census Bureau, we show that, within a marriage market, when a randomly chosen woman becomes more likely to earn more than a randomly chosen man, the marriage rate declines. This relationship continues to hold when we flexibly control for both the distribution of men's income and the distribution of women's income. Moreover, to fully address concerns about omitted variables, we utilize a Bartik-style instrument (Bartik 1991, Aizer 2010). We exploit the fact that historically men and women have tended to work in different industries. Based on the initial industry composition of a state and the industry-wide wage growth at the national level, we create sex-specific predicted distributions of local wages that result from aggregate shifts to labor demand that are plausibly uncorrelated with characteristics of men and women in a particular marriage market. We show that marriage rates decline when the predicted probability that a woman earns more than a man increases.

This result suggests a potential link between two important social developments over the last several decades: the relative increase in women's income (as discussed above) and the decline in marriage rates. Indeed, marriage rates declined substantially in the US, from about 81 percent in 1970 to 51 percent in 2010 for young adults aged 25 to 39.[3] Our estimates imply that the aversion to the situation where the wife earns more than the husband can explain 23 percent of this decline.

[1]Figures 3 and 4, which draw on administrative data, show that this feature of the distribution is not driven by misreporting of income.

[2]Details about our definition of marriage markets and the computation of the counterfactual distributions in Figure 1 are in Section 2.

[3]The fact that marriage rates declined for older individuals as well – from 80 percent to 64 percent among those aged 40 to 65 – suggests that this decline does not solely reflect a change in the timing of marriages.

We then turn our attention from aggregate outcomes to individual couples. We first ask whether a woman whose potential income exceeds her husband's might distort her labor supply. Using 1970 to 2010 data from the US Census Bureau, for each married woman we estimate the distribution of her potential earnings based on her demographics. We show that when the probability that the wife's potential income exceeds her husband's actual income is higher, the wife is less likely to participate in the labor force. Moreover, if she does work, the gap between her realized and potential income is higher. Both of these patterns suggest women distort their labor supply so as to avoid a gender-role reversal in earnings. Of course, an important concern is that women who marry men whose income is below their own potential income have unobservable characteristics that keep them our the labor force or keep their realized income low. We consider two approaches to deal with this concern. First, we show that the key coefficient is stable as we include controls for a number of observable characteristics of the couple. Second, we construct a proxy for relative income at marriage; inclusion of this control does not affect our estimates.

Even though our results suggest that some couples try to avoid having the wife earn more than the husband, this situation has become quite common. Based on the American Community Survey 3-year aggregate (2008 to 2010), the wife earns more than the husband in 26 percent of the couples where both individuals are between 18 and 65 years old. In these couples, does the violation of gender identity norms influence the quality of marriage? Using panel data from the National Survey of Families and Households, we find that the couples where where the wife earns more than the husband report being less happy, report greater strife in their marriage, and are ultimately more likely to get a divorce.

Finally, we examine the relationship between relative income and the division of home production. Using the American Time Use Survey, we show that the gender gap in home production – how much more time the wife spends on non-market work than the husband – is *larger* in couples where the wife earns more than the husband. This result runs counter to standard models of the division of labor within the household (e.g., Becker 1973), which predict a negative relationship between the wife's share of market income and her relative contribution to home production activities. One explanation for the observed pattern is that, in couples where the wife earns more than the husband, the "threatening" wife takes on a greater share of housework so as to assuage the "threatened" husband's unease with the situation. The wife, of course, may ultimately get tired of working this "second shift" (Hochschild and Machung 1989), which could be one of the mechanisms behind our results on divorce.

Since the initial work by Becker (1973, 1974), the economic analysis of marriage markets has made great strides by developing tractable models that abstract from issues such as tradition and identity. Consequently, while empirical work on marriage markets is vast, little of it examines the role of gender identity. Fortin (2005) uses data from the World Values Surveys to assess how gender role attitudes impact women's labor market outcomes in a sample of 25 OECD countries over a 10-year period. She shows that the social representation of women as homemakers and men as breadwinners is associated with a low labor force participation by women and a large gender gap in income. Fortin (2009) examines a similar question in a single country (the US) over a longer time period (1977 to 2006). She shows that the evolution of gender role attitudes over time correlates with the evolution of female labor force participation. In particular, while women's gender role attitudes steadily became less traditional until the mid-1990s (e.g. more and more women disagree with the notion that husbands should be the breadwinners and wives should be the homemakers), these trends reversed in the mid-1990s, precisely at the time that coincides with the slowdown in the closing of the gender gap in labor force participation. Fernandez *et al.* (2004) document intergenerational transfer of attitudes toward gender roles. They show that a woman is more likely to work if her mother-in-law worked, presumably because having had a working mother influences the husband's attitudes toward gender.[4] These papers focus on how the variation in gender attitudes (across countries, across time, and across couples) correlate with women's labor force participation whereas our paper examines the extent to which the overall prevalence of traditional attitudes impacts a wide range of outcomes in the aggregate; in addition to women's labor force participation and the gender gap in income, we study the distribution of relative income within households, marriage rates, division of home production, marriage satisfaction, and divorce.[5]

2 Distribution of relative income

In standard models of the marriage market, men and women match based on how desirable each is relative to others of their gender; in each marriage market, the n^{th} best man pairs up with the n^{th} best woman.[6] In these models, relative income – the share of the household income earned by

[4]Morrill and Morrill (2012) argue that, even though there is a stronger correlation in labor force participation between a mother-in-law and a daughter-in-law than between a mother and a daughter, the data are consistent with a model where the preference transfer channel operates solely from mothers to daughters.

[5]Using administrative data from Denmark, Pierce *et al.* (2012) employ a regression discontinuity design to argue that a husband is more likely to use erectile dysfunction medication if he earns less than his wife.

[6]This is the equilibrium outcome if utility is non-transferable or if the wife's and the husband's qualities are complements. If partner's qualities are substitutes and utility is transferable, then the best man pairs up with the

the wife – plays no role. In this section, we demonstrate that the pattern of who marries whom suggests that couples are indeed sensitive to their relative income.

2.1 Census data from the US

We first analyze the distribution of relative income among young married couples, where the wife is aged 22 to 31 and the husband 24 to 33, using data from the American Community Survey 3-year aggregate (2008 to 2010).[7] We focus on the young couples in order to emphasize the impact of gender identity on marriage formation, rather than its impact on gender-specific evolution of income within marriage (which we study in the next section).[8] We focus on the most recent year because it yields the greatest overlap between the distributions of men's and women's income.[9] In the earlier decades (e.g., 1970 and 1980), there are fewer women whose income exceeds that of many men, so an aversion to forming a couple where the wife earns more than the husband has a smaller impact on the distribution of relative income.[10] In Figure 2, we plot the distribution of relative income in each decade since 1970.

We define $relativeIncome_i$ as $\frac{wifeIncome_i}{wifeIncome_i + husbIncome_i}$ where i indexes the couples, and $wifeIncome_i$ and $husbIncome_i$ are the labor income of the wife and the husband, respectively. We only include couples where both the wife and the husband earn a positive income. In the Census there are many couples where $relativeIncome_i$ is exactly equal to $\frac{1}{2}$, which seems somewhat implausible and is likely to be an artifact of the survey method. (In the administrative data we use in the next two subsections there are not nearly as many couples where the husband and the wife earn the same amount.) Accordingly, we recode those observations using a triangular kernel; this eliminates the "spike" in the distribution of $relativeIncome_i$ at $\frac{1}{2}$.[11] As far as we know, there are no tax-based reasons why couples should care about relative income.[12]

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worst woman and so on.

[7]This corresponds to the youngest age group in our construction of the marriage markets in Section 3.

[8]Results are qualitatively similar if we include all couples regardless of their age.

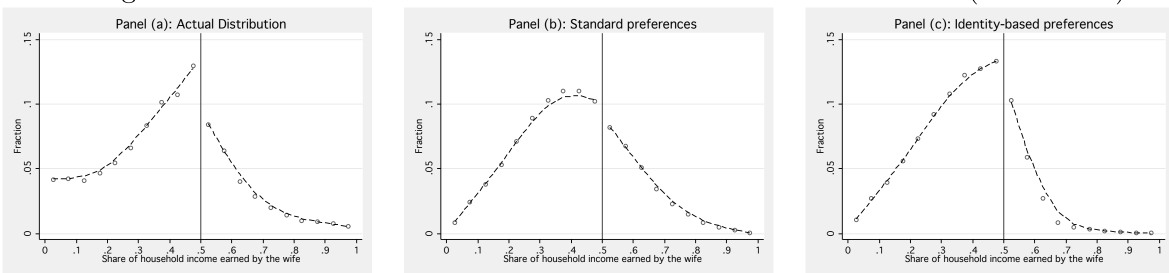
[9]Our results are similar if we use data from 1990 or 2000 instead.

[10]When the distribution of men's income first order stochastically dominates the distribution of women's income in every marriage market, the unique stable matching under the identity-based preferences (as defined below) is positive assortative matching, i.e., the same as under standard preferences. Likewise, under the stochastic matching process we use below, identity-based and standard preferences generate similar counterfactual outcomes in the earlier decades when the distributions of men's and women's income are further apart.

[11]In other words, when we plot a histogram with n bins, bin $k \in \{1, ..., n\}$ is assigned a share $\frac{\frac{n}{2} - \left|\frac{n}{2} - (k-1)\right|}{\frac{n}{2}\left(\frac{n}{2} - 1\right)}$ of the observations whose value is exactly $\frac{1}{2}$.

[12]Changes in marginal tax rate can cause bunching at particular levels of income (Chetty *et al.* 2011), which could in turn cause a husband and wife to choose the exact same income, but the administrative data shows that this is not the source of the spike in the distribution of relative income in the American Community Survey.

Figure 1: Actual and counterfactual distributions of relative income (US Census)

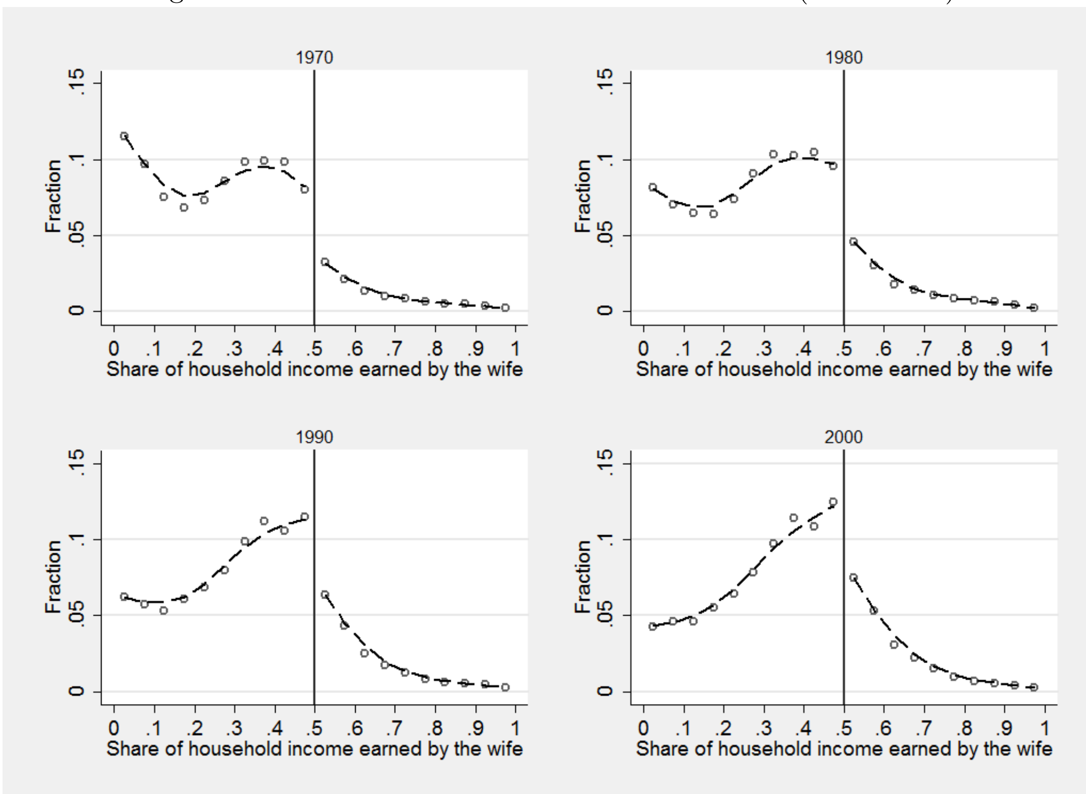


Panel (a) of Figure 1 depicts the histogram of $relativeIncome_i$, along with a local polynomial which is separately estimated for the observations where the wife earns less than the husband and the observations where she earns more. The histogram clearly demonstrates a sharp drop in the density once relative income exceeds $\frac{1}{2}$. This suggests that that couples may have an aversion to the wife earning more than the husband. In Panels (b) and (c) we depict counterfactual distributions of relative income that would arise under standard and identity-based preferences, respectively. For both panels, we use the data on all individuals in the relevant age group, whether married or not. We assign each individual to a marriage market, based on state, race,[13] and a binary education group based on whether they have at least some college education. Then, given ordinal preferences for partners, we run the following algorithm. In each marriage market, a woman and a man are picked at random. The man proposes to the woman with a probability equal to $\frac{N_W-k+1}{N_W}$ where N_W is the number of women in the marriage market and k is the rank of the woman according to the man's preferences. Hence, the man proposes to his favorite woman with probability 1 and to his least favorite woman with probability $\frac{1}{N_W}$. If the man proposes, the woman accepts with a probability equal to $\frac{N_M-k+1}{N_M}$ where N_M is the number of men in the marriage market and k is the rank of the man according to the woman's preferences. If the woman accepts the man's proposal, they are matched and removed from the pool of singles. The algorithm proceeds until the total number of matches is the minimum of the number of married men and the number of married women in that marriage market.

Under standard preferences, we assume that both men and women always prefer a partner with a higher income. Under identity-based preferences, we assume that women always prefer a partner with a higher income, but a man with income h has an ordinal utility for a woman with income w equal to $-|h-w|$. In other words, a man values women's income as long as it does not exceed

[13]The three races we consider are (non-Hispanic) white, (non-Hispanic) black, and Hispanic. We drop individuals of other races.

Figure 2: Distribution of relative income over time (US Census)

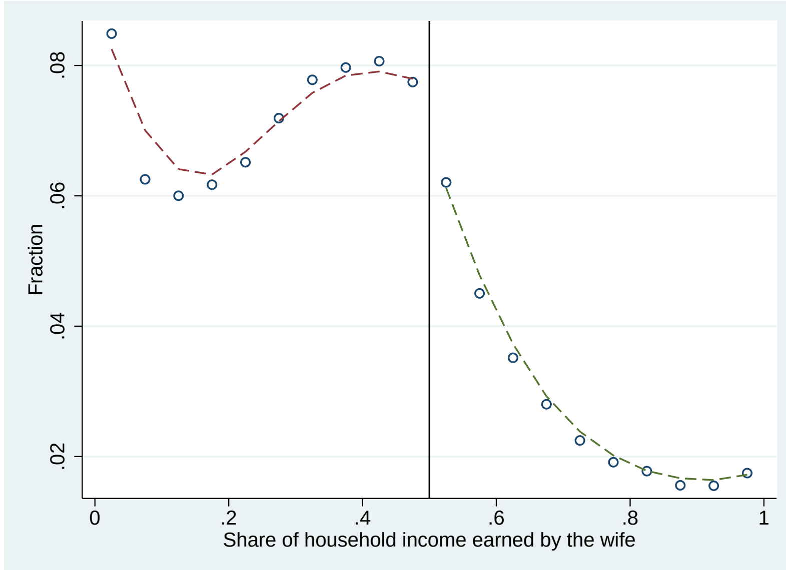


his own. Once a woman earns more than a man, her income becomes a liability rather than an asset. Such preferences are similar to those identified by Fisman *et al.* (2006) in a speed dating setting. They find that a woman always values a man's intelligence and ambition, but a man values a woman's intelligence and ambition only if it does not exceed his own. A man is less willing to date a woman who surpasses him on these attributes.

Panels (b) and (c) make it clear that identity-based preferences generate the key qualitative feature of the actual distribution of relative income, namely the sharp drop in the distribution when a woman earns more than her husband.[14] Unsurprisingly, standard preferences do not exhibit such a drop. Thus, the distribution of relative income suggests an important role of gender identity in marriage formation.

[14]Even though identity-based preferences generate this key qualitative feature of the actual distribution, they do not do a better job of matching the overall distribution. Under the Wasserstein metric, the distance between the distributions in Panels (c) and (a) is not smaller than the distance between the distributions in Panels (b) and (a). Moreover, some other features of the data, such as the relationship between a woman's income and the likelihood that she is married, are not matched well by the counterfactuals based on either the identity-based or standard preferences.

Figure 3: Distribution of relative income (US administrative data)



2.2 Administrative data from the US

One potential issue with Figures 1 and 2 is that income is self-reported. Thus, it is in principle possible that the apparent cliff at 0.5 is due to misreporting.[15] To address this issue, in this subsection we depict the distribution of relative income based on administrative data. In particular, we use the data from the Survey of Income and Program Participation (SIPP) which is linked to administrative data on income from the Social Security Administration and the Internal Revenue Service.[16] SIPP consists of a series of national panels, each representative of the US civilian, noninstitutionalized population. For each married couple, we use the observation from the first year that the couple is in the panel. We include all married couples where both the husband and the wife earn positive income and are between 18 and 65 years of age. This leaves us with 73,654 couple-level observations. The data includes observations from 1984 to 2004. For both the husband and the wife, the measure of their individual income is total labor and self-employment income.

The distribution of relative income is qualitatively the same as in Figures 1 and 2. Most importantly, the distribution exhibits a sharp drop at the point where the wife starts to earn more than the husband.

[15]For misreporting to generate the pattern in Figure 1, it would need to be the case that the respondents are less willing to say that the wife earns more than the husband, which by itself would suggests the importance of gender identity. Still, we wish to show that gender identity influences actual relative income rather than only the self-reports.

[16]Specifically, SIPP Synthetic Beta program allows researchers to directly access a version of the dataset with "synthetic" (i.e., imputed) income variables. The Census Bureau then validates the results obtained with synthetic data by running the same computer code on the original, confidential data. Validated results can be released to the public. Figure 3 is based on the administrative records rather than the synthetic data.

2.3 Administrative data from Canada

Figures 1, 2, and 3 all group relative income into twenty bins. This coarse grouping is necessary given the somewhat limited sample size. With a much larger dataset, we would be able to group relative income into more bins and thus have a more "microscopic" view of the distribution and how it changes around 0.5. To this end, we utilize the Longitudinal Administrative Data Dictionary (LAD). LAD is a 20% representative panel of all taxfilers in Canada. It contains administrative information on all taxable income. We utilize data from 1983 to 2006.[17]

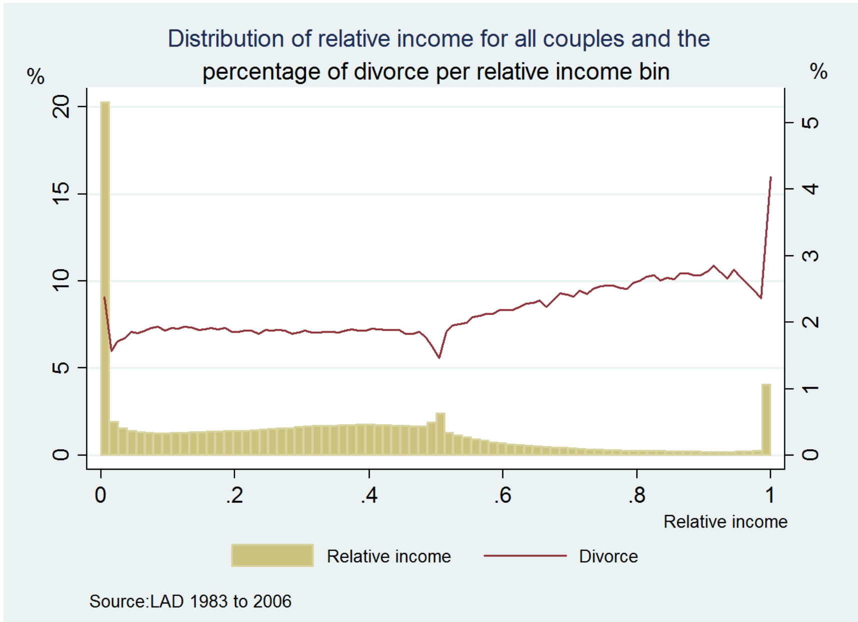
We construct a dataset where the level of observation is couple by year. We include all married couples as long as at least one individual in the couple has strictly positive income. Our sample thus includes over 60 million couple-year observations. Each person's income is defined as their total income, inclusive of labor income, investment income, pensions, net business income and other sources. We recode any strictly negative individual income as zero. The histogram in Figure 4 depicts the distribution of relative income with the fraction of couple-years in each of the 100 bins indicated on the left vertical axis. Note that, unlike in the previous figures, couples where the wife or the husband has no income are included. As in the US data, Figure 4 indicates a sharp decrease in the number of couples once the wife's income exceeds the husband's.

Figure 4 also shows how the likelihood that a couple becomes divorced varies with relative income. The line depicts (on the right vertical axis) the fraction of couples who divorce during a given year. In particular, we code a couple-year i, t as divorcing in year t if the couple was married in year t and both spouses are alive but not married to each other in year $t + 1$. Remarkably, divorce rate seems independent of relative income as long as the wife earns less than the husband, but once the wife earns more than the husband, the divorce rate increases with relative income.[18] The magnitude of the increase is also substantial, with the divorce rate rising from around 2 percent per year to 3 percent per year, but this pattern should be interpreted with caution since we are not including controls for any other variables, such as the wife's or the husband's individual income or age. In Section 5 we will further explore the relationship between relative income and marital stability, albeit using a much smaller sample and a non-administrative measure of income.

[17] The advantages of this dataset relative to both the American Community Survey and SIPP are clear, but LAD has its disadvantages as well. In particular, we were unable to gain direct access to the data or write our own code to conduct the analyses. All of the analysis was conducted by research assistants employed by Statistics Canada. Due to logistical obstacles with LAD we focus on publicly available US datasets for most of the paper, but in this subsection we use the Canadian data to generate a more precise distribution of relative income.

[18] There is also a curious small spike in the distribution of relative income and a dip in the likelihood of divorce at the point where the wife and the husband earn exactly the same amount. We suspect there is some omitted factor (e.g., the couple owns a business together) that accounts for this.

Figure 4: Distribution of relative income and divorce (Canada)



3 Marriage rates and relative income

For the last forty years, marriage rates in the United States have been steadily declining. Between 1970 and 2008, the fraction of young adults who are currently married steadily decreased by 30 to 50 percentage points among all race, gender and education groups (Autor, 2010).[19] Over the same period, women's income has greatly increased relative to that of men's. Results from the previous section suggest a potential link between these two trends: if men or women dislike unions where the husband earns less than the wife, as women command a greater share of labor income, marriages may become less appealing and thus less common. The lower prevalence of marriage could be due to men or women choosing not to get married or due to the dissolution of existing marital unions.

In this section, we analyze how the share of individuals who are currently married varies with the relative distribution of men's and women's potential earnings. Throughout the section, we use 1970 to 2000 data from the US Census and the American Community Survey 3-year aggregate (2008 to 2010). We assign individuals to marriage markets based on the pattern of homophily in marriage: most marriages occur between men and women who are of the same race and are

[19] Part of this decrease is due to delay in marriage, but the fraction of older adults who are married has also been declining.

of similar age and education.[20] Moreover, marriages tend to form between individuals who live close to each other. Accordingly, we define marriage markets based on the state of residence, race, age group, and education group. The three race groups we consider are (non-Hispanic) whites, (non-Hispanic) blacks, and Hispanics.[21] The three age groups are (i) 22 to 31 for women and 24 to 33 for men (ii) 32 to 41 for women and 34 to 43 for men and (iii) 42 to 51 for women and 44 to 53 for men. The two education groups are (i) high school degree or less and (ii) some college or more. Appendix Table 1 documents sorting along these dimensions. For example, 98% of wives who are white are married to a husband who is white,[22] 73% of wives with a high school degree or less are married to a husband with similar educational qualifications,[23] and 76% of wives aged 22 to 31 are married to a husband aged 24 to 33.[24] Overall, 56% of all marriages are between a man and woman from the same marriage market.

Given a particular marriage market, we wish to know how the changes in women's income relative to that of men affect marriage market outcomes. For each marriage market m and year $t \in \{1970, 1980, 1990, 2000, 2010\}$ we compute how likely it is, when a woman encounters a man, that her income exceeds his. Specifically, given woman i and man j, consider a binary variable that takes value 1 if i's income exceeds j's. We define $PrWomanEarnsMore_{mt}$ as the mean of this variable taken across all possible couples. Operationally, we construct this variable by randomly drawing 50,000 women and men with replacement and computing the share of couples where the woman earns more than the man.

We consider several measures of income. First, we use individuals' actual earnings, where we code an individual as having zero income if he or she is not in the labor force. Second, we construct a measure of predicted earnings based on demographic characteristics. In particular, within each marriage market, we assign each woman and man in a census year to a demographic group defined based on age (three-year intervals), education (less than high school, high-school, some college, college, more than college), race, and state of residence. We then assign potential income to each individual by drawing from the earnings distribution within those in the individual's demographic group who have positive income. Finally, for our preferred specification, we construct distributions of relative income based on a Bartik-style instrument to isolate the variation in relative income

[20] Our approach to classifying marriage markets is similar to that used in Charles and Luoh (2010) and Loughran (2002).

[21] We drop individuals of other races.

[22] The fraction of married women in a same-race marriage is 97% and 82% for blacks and Hispanics, respectively. For a broader discussion of same-race marriages in the United States, see Fisman *et al.* (2008).

[23] This fraction is 76% for wives with some college or more.

[24] These fractions are 70% and 68% for the other two age groups.

which is plausibly unrelated to the factors that directly affect the marriage market.

Across all census years and marriage markets, the likelihood that a randomly chosen woman earns more than a randomly chosen man is about 0.25 (using either measure of income). This likelihood has increased steadily over time, going from 11-14% in 1970 to about 31-32% in 2010.[25] More importantly for our purposes, these dynamics have varied across marriage markets.[26] Thus, there is ample variation in $PrWomanEarnsMore_{mt}$ even when we include marriage market and year fixed effects. Note that this residual variation stems both from compositional shifts within a marriage market over time and from shocks that differentially affect men and women within a marriage market. When we turn to our instrumental variables approach, we will isolate the component of the latter source of variation which stems for US-wide changes in labor demand across industries.

Our baseline OLS specification is the following:

$$\begin{aligned} MaleMarried_{mt} &= \beta_1 \times PrWomanEarnsMore_{mt} \\ &+ \beta_2 \times lnWomensIncome_{mt} + \beta_3 \times lnMensIncome_{mt} \\ &+ \delta_t + \delta_t \times AgeGroup_m + \delta_t \times EduGroup_m + \delta_t \times Race_m + \delta_t \times State_m \\ &+ \alpha_m + \epsilon_{mt} \end{aligned} \tag{1}$$

The unit of observation is a marriage market in a census year. $MaleMarried_{mt}$ is the share of males who are currently married.[27] Variables $lnWomensIncome_{mt}$ and $lnMensIncome_{mt}$ are the logs of the average female and male income, respectively. All specifications include marriage market fixed effects (α_m) and year fixed effects (δ_t) interacted with the age group, the education group, the race, and the state of residence. Inclusion of marriage market fixed effects controls for any time-invariant unobserved differences across marriage markets. Inclusion of year fixed effects controls for any aggregate temporal variation in marriage rates. We also include the interaction of year fixed effects with the demographic determinants of the marriage market because the relationship between these demographic variables and marriage rates may have changed over time. Standard errors are clustered by state and each observation is weighted by the number of women in the marriage market.

[25]See Appendix Table 2 for summary statistics.
[26]See Appendix Table 3.
[27]We get similar results if we use the share of females who are married.

This baseline specification is in Column (1) of Table 1. The estimate of β_1 is -0.181 and is marginally significant ($p = 0.078$). Column (2) includes a set of additional marriage market by year controls: the sex ratio, male and female incarceration rate, average years of schooling for men and women, and the number of men and women in the market. With this specification, the estimated effect becomes stronger $\left(\hat{\beta}_1 = -0.307\right)$ and highly significant ($p < 0.01$). Finally, in Column (3) we control for men and women's income more flexibly, including the income at each decile, i.e., the 10th to 90th percentile of the distribution of both men and women's income in the marriage market that year. The estimate of β_1 is -0.192 ($p < 0.05$). Thus, all three specifications point to the importance of gender identity in individuals' decision on whether to get married.

In Columns (4) through (6) we consider the same three specifications, but we construct the variable $PrWomanEarnsMore_{mt}$ using potential income. Once again, the estimate of β_1 is consistently negative. Moreover, the estimate is very stable across the three specifications, ranging from -0.214 to -0.199, and always highly significant ($p < 0.01$).

The identifying assumption behind these specifications is that $PrWomanEarnsMore_{mt}$ is uncorrelated with unobserved shocks to factors that might influence marriage rates. The robustness of our estimates to the inclusion of flexible controls for the distribution of men and women's income (Columns (3) and (6)) ameliorates concerns about many omitted variables, but to provide further support for our causal interpretation, we now turn to an instrumental variables approach.

Historically, men and women have tended to work in different industries (e.g. women are overrepresented in services and men in construction and manufacturing). Based on the industry composition of the state and the industry-wide wage changes at the national level, we can thus isolate sex-specific variation in local wages that is driven solely by aggregate labor demand, which is presumably uncorrelated with the characteristics of workers in a given marriage market level. This approach builds on previous work by Bartik (1991) and Aizer (2010). In contrast to previous uses of the "Bartik instrument," which focus on changes in *average* wages, we construct an instrument for the entire *distribution* of potential income in each marriage market.

We begin by calculating average yearly wages by gender and marriage market as follows:

$$\bar{w}^g_{mt} = \sum_j \gamma^g_{resj,b} \times w^g_{reajt,-s}$$

where g indexes gender, r race, e education-group, a age-group, s state, j industry[28] and t census

[28] We consider 12 industry groups: (1) Agriculture (2) Mining (3) Construction (4) Manufacturing (5) Transporta-

year. Variable $w^{g}_{reajt,-s}$ is the average wage in year $t \geq b$ in industry j for workers of a given gender, race, education and age-group in the nation, excluding state s. Variable $\gamma^{g}_{resj,b}$ is the fraction of individuals with gender g, race r, and education e in state s who are working in industry j, as of the base-year b.

We consider two base years, 1970 and 1980. Using 1970 provides an additional decade of data, yielding a greater sample of marriage markets. The 1970 Census has many fewer observations than the 1980 Census,[29] however, so the estimates of $\gamma^{g}_{resj,b}$ are less noisy when we use 1980 as the base year. We report results using both base years.

Variable $\bar{w}^{g}_{mt}$ is strongly correlated with the actual mean income of gender g in marriage market m in year t: states that initially had relatively more women in industries that subsequently experienced wage growth at the national level tend to have more growth in women's income relative to that of men. But, unlike the variation in actual income, variation in $\bar{w}^{g}_{mt}$ over time is driven by aggregate shocks and is thus plausibly orthogonal to factors that might directly influence marriage rates in market m.

Similarly, we wish to construct a measure of the entire distribution of income by gender which is driven solely by aggregate shocks. We modify the standard Bartik instrument to compute predicted yearly wages at the $p = \{5th, 10th, 15th, ..., 90th, 95th\}$ percentile.

Specifically, let

$$\bar{w}^{g,p}_{mt} = \sum_{j} \gamma^{g}_{resj,b} \times w^{g,p}_{reajt,-s}$$

where $w^{g,p}_{reajt,-s}$ is the p^{th} percentile of the national income distribution in year t in industry j for workers of a given gender, race, education and age-group, excluding state s. *A priori*, it is not clear that $\bar{w}^{g,p}_{mt}$ will be correlated with the p^{th} percentile of gender g's distribution in market mt. For example, if half the women in a demographic group m work in some industry j^{high} where the *minimum* income is y^{high} and half the women in m work in some industry j^{low} where the *maximum* income is $y^{low} < y^{high}$, increase in the 5th percentile of wages in industry j^{high} will not raise the 5th percentile of wages of women in market m. This example, however, has little empirical relevance – *a posteriori* it turns out that the distributions defined by $\{\bar{w}^{g,p}_{mt}\}_p$ indeed correlate with the actual distributions of income. In other words, the Bartik instrument has a strong "first stage" when it is used to predict how the distribution of potential income varies across markets.[30]

tion (6) Wholesale Trade (7) Retail Trade (8) Finance, Insurance and Real Estate (9) Business, Personal and Repair Services (10) Entertainment and Recreation Services (11) Professional Services (12) Public Administration.

[29] The 1970 Census is based on a 1% sample whereas the 1980 Census is based on a 5% sample of the population.

[30] Appendix Table 4 reports the first-stage regression estimates of the mean and selected percentiles of predicted

This modification to the standard Bartik measure allows us to construct a measure of $PrWomanEarnsMore_{mt}$ whose variation over time is orthogonal to local labor market conditions. Specifically, we draw from the distributions defined by $\{\bar{w}^{g,p}_{mt}\}_p$, and calculate the likelihood that a randomly chosen women earns more than a randomly chosen man. Column (7) reports the baseline specification from Equation (1) using $\bar{w}^{g}_{mt}$ and $\bar{w}^{g,p}_{mt}$ with the 1970 base year to construct measures of $PrWomanEarnsMore_{mt}$, $lnWomensIncome_{mt}$, and $lnMensIncome_{mt}$. As in other specifications, the estimate of β_1 is negative and significant ($p < 0.01$). Moreover, given this estimate $\left(\hat{\beta}_1 = -0.438\right)$, the effect of the likelihood that a woman earns more than a man on marriage rates is economically significant. A 10 percentage point increase in this likelihood decreases marriage rates by 4.4 percentage points. In Column (8) we include a set of additional marriage market by year controls. The estimate declines to -0.317, but remains significant at the 1% level. Finally, in Column (9), we include controls for the predicted yearly wages of the 10th to 90th percentile for wives and husbands in the marriage market market that year. The estimate of $\hat{\beta}_1$ declines to -0.234 and is no longer statistically significant. Nevertheless, the magnitude of the estimate remains sizable and is economically significant (the magnitude is similar to that of the baseline specification using predicted earnings in Column (4)). Finally, in Columns (10)-(12) we consider the same specifications as in Columns (7)-(9) but with 1980 as the base year for the Bartik instrument. All of the estimates are again negative and statistically significant ($p < 0.05$ for all specifications).

Taken together, these results highlight the importance of the relative distribution of men and women's income in marriage markets. The estimate from our preferred specification (Column (12)) implies that the secular increase in the aggregate likelihood that a woman earns more than a man explains 23 percent of the decline in the rates of marriage from 1970 to 2010.[31]

Note that the relative distribution of men and women's income might influence the formation of marriage even in the absence of gender identity considerations. In Beckerian models of the marriage market, one of the key benefits of marriage is specialization. Specialization, in turn, is more valuable if a man and a woman have different opportunities in the labor market. As $PrWomanEarnsMore$ increases, there are smaller "gains from trade" that can be achieved through marriage. This force alone might account for our negative estimate of β_1. That said, evidence we present in other sections of this paper is in direct conflict with the standard models of the marriage market. For

$lnMensIncome$ and $lnWomensIncome$ on the corresponding moments of the 1970 Bartik predicted $lnMensIncome$ and $lnWomensIncome$. The coefficient estimates range from 0.4 to 1 and are all significant at the 1% level. The first-stage regressions using the 1980 Bartik are similar.

[31] The coefficient -0.347 multiplied by the 20 percentage point increase in $PrWomanEarnsMore$ (Appendix Table 2) is 23% of the 30 percentage point decrease in marriage rates.

example, the relationship between relative income and the division of household chores (Section 6) is the opposite of what one would expect in the absence of gender identity considerations. Thus, the view that couples have an aversion to the wife earning more than the husband provides a more parsimonious explanation of the various patterns we present in this paper.

4 Women's labor supply and relative income

The previous sections establish that couples where the wife's potential income would exceed the husband's are less likely to form. When such couples do form, we might expect gender identity to distort labor market outcomes. In particular, a wife who, were she to join the workforce, would be threatening to her husband (because her income would exceed his) may end up staying at home or she may distort her labor supply in other ways – e.g., work fewer hours or take a job that is less demanding and pays less. In this section we analyze such potential distortions in the wife's labor force participation and labor market outcomes.

Throughout this section, we use data on married couples from the 1970 to 2000 US Census and the American Community Survey 3-year aggregate (2008 to 2010). We restrict the sample to those couples where the husband is working and both the wife and the husband are between 18 and 65 years of age. For each couple i, we estimate the distribution of the wife's potential earnings as follows. For $p \in \{5, ..., 95\}$,we define w_i^p as the p^{th} percentile of earnings among working women in the wife's demographic group that year. We assign the demographic group based on age (five-year intervals), education (less than high school, high-school, some college, college, more than college), race, and state of residence. We then define a variable $PrWifeEarnsMore_i = \frac{1}{19}\sum_p \mathbf{1}_{\{w_i^p > husbIncome_i\}}$ where $husbIncome_i$ is the husband's income. Thus, whether the wife works or not, $PrWifeEarnsMore_i$ captures the likelihood that she would earn more than her husband if her income were a random draw from the population of working women in her demographic group.[32]

Summary statistics for this sample are presented in Appendix Table 5. Across all census years, the mean of $PrWifeEarnsMore_i$ is 0.18. Not surprisingly, this probability has increased monotonically over time, from 0.09 in the 1970 census to 0.26 in the 2010 census. Across all years, about 66 percent of wives are participating in the labor force. As we mentioned in the introduction, wives'

[32] As we discuss in Subsection 4.2, the income of the women who do work may also be distorted by gender identity considerations. Thus, the distribution of income we identify is not the distribution of potential income, as it is usually construed, but rather the distribution of the income that the wife would likely earn were she to join the labor force.

labor participation increased steeply between 1970 and 1990 (going from 44 percent to 70 percent), but has essentially reach a plateau since 1990, with about 74 percent of wives being in the labor force in 2010.

4.1 Labor force participation

We first examine wives' labor force participation. One of the strongest ways to conform to traditional gender roles is for the wife to stay at home while the husband plays the role of breadwinner. Might it be the case that when gender identity is threatened by the possibility that the wife would be the primary provider (in a sense that her income would exceed the husband's), some couples retreat to traditional gender roles? Given a couple i, let $wifeLFP_i$ be a binary variable equal to 1 if the wife is in the labor force.

In Column (1) of Table 2, we consider, as the baseline specification, a linear probability model

$$\begin{aligned} wifeLFP_i &= \beta_0 + \beta_1 \times PrWifeEarnsMore_i \\ &\quad + w_i^p + \beta_2 \times lnHusbIncome_i + \beta_3 \times X_i + \varepsilon_i \end{aligned}$$

where $lnHusbIncome_i$ is the logarithm of husband's income, w_i^p are controls for the wife's potential income at each of the vigintiles and X_i represents non-income controls: year fixed effects, state fixed effects, the wife and the husband's race, the wife and the husband's 5-year age-group, and the wife and the husband's education group.[33] Standard errors are clustered by the wife's demographic group (which pins down the distribution of her potential income). The baseline estimate of β_1 is -0.254 ($p < 0.01$).

The husband's income might impact the marginal utility of household income non-linearly, so in Column (2) we include a cubic polynomial in $lnHusbIncome_i$. The estimate of β_1 falls but remains economically and statistically significant at -0.182 ($p < 0.01$). Also, the impact of the wife's potential income on her labor supply might interact with the husband's income for reasons that are separate from the couple's concern that she will earn more than he does. Accordingly, in Column (3) we add a control for the median of the wife's predicted income $\left(w_i^{50}\right)$ interacted with the income of the husband. The estimate of β_1 is unaffected.

[33] We use five education categories - less than high school, high school, some college, college degree and more than a college degree.

The main concern is that a woman who is willing to marry a man whose income is below her potential income might have unobservable characteristics that keep her out of the labor force. For example, highly educated women that marry men with lower education and low earnings might be systematic underachievers or systematically lack confidence to participate in the labor market; such women might be relatively more drawn towards home production and child-rearing activities. We consider two approaches to deal with this concern.

First, we examine the sensitivity of $\hat{\beta}_1$ to the inclusion of other controls. In Column (4), we include as a control an indicator variable that equals 1 if the wife reports having had any child. In Column (5) we include indicator variables for the full interaction of the wife's demographic group and the husband's demographic group. The inclusion of these additional controls essentially leaves the estimate of β_1 unchanged. The fact that our estimate appears very stable across specifications suggests that, to the extent that the observable characteristics in our data are representative of unobservables, the negative value of $\hat{\beta}_1$ is not due to an omitted variable bias (Altonji *et al.* 2005).

Second, focusing on the data from the American Community Survey, we attempt to isolate the variation in $PrWifeEarnsMore_i$ that is driven by changes in relative income that took place after the couple got married. Unlike the earlier Census data, the American Community Survey contains information on the year of current marriage. We proxy for relative income of spouses at the time of marriage as follows. For each couple, we let t_m be the census year that is the closest to the year of marriage. (We drop couples for whom the difference between the year of marriage and the closest available census year is more than 5 years.) We then construct the distribution of potential income, in year t_m, for both the husband $\{h_i^p\}$ and the wife $\{w_i^p\}$, using the same procedure as above. Based on these two distributions, we define a variable $PrWifeEarnsMoreAtMarriage_i = \frac{1}{361}\sum_p \sum_q \mathbf{1}_{\{w_i^p > h_i^q\}}$, which captures the probability that, based on the couples' demographics, the wife's potential income exceeded that of the husband at the time of marriage.

We first replicate the specification from Column (2) for each decade (Columns (6) - (10)) and for the subsample of the 2010 sample for which we can construct relative earnings at marriage (Column (11)). Our main specification is in Column (12), where we include as controls $PrWifeEarnsMoreAtMarriage_i$ and the vigintiles of the potential earnings for both the husband and the wife at marriage. With these controls, the estimate of β_1 stems from variation in $PrWifeEarnsMore_i$ that is driven by the *changes* in the wife's and the husband's relative income since marriage. This specification thus mitigates first-order concerns about selection.[34] Compari-

[34]Two concerns still remain. First, our proxy for relative income at marriage is imperfect as we do not know the

son of Columns (11) and (12) shows that the estimate of β_1 is unaffected by the inclusion of these controls. Overall, while we do not have an exogenous source of variation in $PrWifeEarnsMore_i$, the data suggest that married women may sometimes stay out of the labor force so as to avoid a situation where they would become the primary breadwinner.

Columns (6) through (10) allow β_1 and the coefficients on the control variables vary across the decades. This is potentially important as factors that influence women's labor supply might change over time. For each time period, we find a negative and statistically significant relationship between the likelihood that the wife is in the workforce and the likelihood that she would earn more than her husband were she to work. The estimate of β_1 peaks (in absolute value) in 1980 and appears to be declining over time. One possible interpretation of this trend is that gender identity considerations played a larger role in the earlier decades.

Based on the pooled sample in Column (2), a 10 percentage point increase in the probability that a wife would earn more than her husband reduces the likelihood that she participates in the labor force by 1.8 percentage points. Put differently, a one standard deviation (across all years) increase in the probability that a wife would earn more than her husband reduces the likelihood that she participates in the labor force by 4.5 percentage points.

4.2 Gap between potential and realized income

Having the wife leave the labor force is a very costly way to restore traditional gender roles. It would be less costly for the wife to simply reduce her earnings to a level that does not threaten the husband's status as the primary breadwinner. In this subsection, we present evidence for such behavior.

Given a couple i, let $incomeGap_{ij} = \frac{wifeIncome_i - wifePotential_i}{wifePotential_i}$ where $wifePotential_i$ is simply the mean of the distribution of potential earnings for the wife, as defined in the previous subsection. To emphasize the distortions in income for women who do not leave the workforce, we focus on the sample of couples where the woman is working. These results are reported in Table 3, which follows exactly the same structure as Table 2.

In particular, in Column (1) of Table 3, we consider the following baseline OLS specification:

couples' actual income at the time. Second, to the extent that couples can predict how their relative income will evolve after marriage, some concerns about selection are still present.

$$\begin{aligned} incomeGap_i &= \beta_0 + \beta_1 \times PrWifeEarnsMore_i \\ &\quad + w_i^p + \beta_2 \times lnHusbIncome_i + \beta_3 \times X_i + \varepsilon_i. \end{aligned}$$

The estimate of β_1 is -0.094 ($p < 0.01$). Including a cubic polynomial of $lnHusbIncome_i$ in Column (2) strengthens the effect: $\hat{\beta}_1 = -0.174$ ($p < 0.01$). Women that are more threatening to their husband given their potential systematically underperform in the labor market. A 10 percentage point increase in the probability that a wife would would earn more than her husband increases the gap between her actual earnings and her potential earnings by 1.7 percentage points. Put differently, a one standard deviation increase in this probability increases the gap between actual and potential earnings by 4.4 percentage points.

Columns (3)-(12) of Table 3 consider the same robustness checks as in the previous subsection. In Column (3) we add an interaction between the median of the wife's potential income and the husband's income. In Column (4) we further include an indicator variable that equals 1 if the wife reports having had a child. In Column (5), we include fixed effects for the wife's demographic group dummies interacted with the husband's demographic group dummies. Columns (2) to (5) show that the coefficient is quite stable once we include a polynomial control for the husband's income.

In Columns (6) to (10), we present estimates of β_1 separately by year. The estimate of β_1 varies somewhat across decades, but, unlike in Table 2, no obvious trend over time emerges from the data.

In Columns (11) and (12), we assess the sensitivity of $\hat{\beta}_1$ in 2010 to including controls for $PrWifeEarnsMoreAtMarriage_i$ and the vigintiles of the potential earnings for the husband and the wife at marriage. As we mentioned in the previous subsection, the estimate of β_1 in Column (12) stems from variation in $PrWifeEarnsMore_i$ that is driven by the changes in the wife's and the husband's relative income since marriage. The impact of $PrWifeEarnsMore_i$ on $incomeGap_i$ remains negative and statistically significant.

To supplement this analysis, in Appendix Table 6, we also consider the wife's working hours as an alternative outcome of interest. In particular, in columns (1) and (2) of Appendix Table 6, we replicate the econometric specifications in columns (4) and (5) of Table 3, respectively, using the logarithm of the wife's reported hours worked in the prior week, $lnHoursWorked_i$, as the dependent variable. We restrict the sample to couples for which $incomeGap_i$ is non-missing. We find a negative and statistically significant relationship between $lnHoursWorked_i$ and $PrWifeEarnsMore_i$. A 10 percentage point increase in the probability that a wife would would earn more than her husband decreases her working hours by about 0.6 percentage points. In the remaining columns of Appendix Table 6, we show that this labor supply response on the intensive margin may account for about a third of the negative relationship between $incomeGap_i$ and $PrWifeEarnsMore_i$.[35]

In summary, women's labor supply decisions seem to be distorted in situations where there is a threat that they might become the primary bread winner. In the next section we document some of the costs that arise when the woman does end up earning more than the husband. The presence of these costs provides a potential "rationalization" for the labor market distortions that we document here.

5 Marital stability and relative income

Does relative income affect marital stability? To address this question, we exploit the rich information on marital satisfaction and marital outcomes from the National Survey of Families and Households (NSFH). The NSFH is a nationally representative survey of US households and includes approximately 9,500 households that were followed over three waves from 1988 to 2002. We use data from the first two waves (1987-88 and 1992-94) of the survey.[36] We restrict our analysis to couples where both the wife and the husband are between 18 and 65 years old and at least one person in the household has positive income. Our sample consists of approximately 4,000 married couples.

The NSFH has three questions on marital stability. One asks: "Taking things all together, how would you describe your marriage?" Respondents can choose answers from a scale of 1 (very unhappy) to 7 (very happy). Close to 50% of wives and husbands reported being "very happy" in their current marriage. We define a binary variable $happyMarriage_i$ that indicates whether the answer is "very happy." The second question asks: "During the past year, have you ever thought that your marriage might be in trouble?" We define a binary variable $marriageTrouble_i$ that indicates an affirmative response. The third question asks: "During the past year, have you and your husband/wife discussed the idea of separating?" We define a binary variable $discussSeparation_i$

[35] Columns (3) and (4) of Appendix Table 6 replicate columns (4) and (5) of Table 3 on the subsample of couples for which $lnHoursWorked_i$ is non-missing. Columns (5) and (6) of Appendix Table 6 further include $lnHoursWorked_i$ as an additional control.

[36] We do not use the third wave of the NSFH since it employs only a subsample of the original respondents, excluding, among others, all those couples that were separated or divorced since Wave 2. It is not possible to determine whether a couple is missing from the Wave 3 sample due to separation/divorce or other factors.

that indicates whether the answer is affirmative.

The NSFH also provides information on the wife's and the husband's labor income,[37] on the basis of which we define self-explanatory variables $lnWifeIncome_i$, $lnHusbIncome_i$, and $lnTotIncome_i$.[38] For each couple we also compute $relativeIncome_i$, the share of the household income earned by the wife. In Wave 1, the mean of $relativeIncome_i$ is 0.27 and it exceeds $\frac{1}{2}$ in 15% of households. We define $wifeEarnsMore_i$ as a binary variable equal to 1 if $relativeIncome_i > \frac{1}{2}$. Summary statistics for the main variables used in the analysis are in Appendix Table 7.

In Table 4, we examine how the relative income within the household affects answers to these survey questions. Our baseline specification is a linear probability model

$$\begin{aligned} Y_i &= \beta_0 + \beta_1 \times wifeEarnsMore_i \\ &\quad + \beta_2 \times lnWifeIncome_i + \beta_3 \times lnHusbIncome_i + \beta_4 \times lnTotIncome_i + \beta_5 \times X_i + \varepsilon_i \end{aligned}$$

where Y_i is the answer to the survey question, X_i represents non-income controls: region fixed effects,[39] indicator variables for whether the wife is working, whether the husband is working, the wife and the husband's race and education groups, and a quadratic in the wife's and the husband's age.[40] As Column (1) of Table 4 shows, the wife tends to be less happy with the marriage, is more likely to report that her marriage is in trouble and is more likely to have discussed separation in the past year if she earns more than her husband. In Column (2), we add more flexible income controls, namely cubic polynomials of $lnWifeIncome_i$ and $lnHusbIncome_i$. The estimate of β_1 is unaffected. Since gender identity is more plausibly associated with a prescription that "the husband should earn more than the wife" than with a prescription that "it is better for the wife to earn 20% rather than 30% of the household income," the gender identity explanation for $\hat{\beta}_1 < 0$ implies that the variation in $relativeIncome_i$ that does not change the value of $wifeEarnsMore_i$ should have a lesser effect on happiness. Accordingly, in Column (3) we include $relativeIncome_i$ as an additional

[37]The earnings measures include the wage, salary and self-employment income. In the NSFH, the income information was collected via self-administered questionnaires completed separately by the main respondent and his/her spouse. When possible, the questionnaire was given to the spouse at the beginning of the main interview, to be conducted in another room. If this was not possible, the questionnaire was left in a sealed envelope for the spouse to complete at a later time. See http://www.ssc.wisc.edu/cde/nsfhwp/nsfh1.pdf for further details.

[38]Both in this and in the next section, we set $lnWifeIncome = -1$ if the wife's income is equal to zero and in all regressions we include an indicator variable for whether the wife's income was zero. We apply the same procedure for the husband's income.

[39]State identifiers are not available in the public-use version of the NSFH.

[40]We weight the observations using the couple-level weights. The NSFH provides two sets of weights; a person-level weight and a couple-level weight. Results are similar whether we use no weights, person-level weights, or couple-level weights.

control to the baseline specification. The impact of $wifeEarnsMore$ on $happyMarriage$ is now somewhat smaller and is no longer statistically significant, but the impact on the other two survey questions, $marriageTrouble$ and $discussSeparation$ is unaffected. Taken together, it seems that relative income within a household matters only if it makes the wife the primary breadwinner.

In Columns (4)-(6) we consider the same three specifications, but with the husbands' responses to the same questions as the outcome variable. The results are largely similar. Finally, in the last three columns of table 4, we pool the wives' and the husbands' responses. In these specifications, we include an indicator variable for whether the respondent is the wife or the husband and we cluster standard errors at the level of the couple. In our preferred specification (Column (9)), we find that if the wife earns more than the husband, spouses are 7 percentage points (15%) less likely to report that their marriage is very happy, 8 percentage points (32%) more likely to report marital troubles in the past year and 6 percentage points (46%) more likely to have discussed separating in the past year.

At first thought, one might be tempted to use the difference between the coefficients on the wives' and the husbands' responses to determine whether it is the wife or the husband who dislikes the reversal of traditional gender roles. We suspect that such a comparison is not particularly useful. If say the husband is initially the one who is unhappy, he may start to behave in the ways that make the wife unhappy, perhaps even more so. Such a possibility echoes Al Roth's Iron Law of Marriage: you cannot be happier than your spouse (Roth 2008).

Next, we turn away from survey data to the revealed stability of marriage. For each couple in Wave 1 (1987-88), we construct a binary variable $divorced_i$ which is equal to 1 if the couple is separated or divorced when they are re-interviewed[41] in Wave 2 (1992-94). In Column (1) of Table 5, we consider the baseline linear probability model:

$$\begin{aligned} divorced_i &= \beta_0 + \beta_1 \times wifeEarnsMore_i \\ &\quad + \beta_2 \times lnWifeIncome_i + \beta_3 \times lnHusbIncome_i + \beta_4 \times lnTotIncome_i + \beta_5 \times X_i + \varepsilon_i \end{aligned}$$

where all of the independent variables are measured in Wave 1. In Column (2), we control more flexibly for the wife's and the husband's earnings (Column (2)). In both specifications we find that when the wife earns more than the husband, the likelihood of divorce increases by about

[41] One concern is that there may be selective attrition in the sample by divorce status. If divorced couples are less likely to remain in the panel, we would underestimate the overall tendency to divorce, but the estimate of our key coefficient would be unaffected. Moreover, we find that there is no relationship between attrition and measures of marital stability. The overall attrition rate is about 10%.

6 percentage points ($p < 0.05$). Since 12% of couples in the sample get divorced by Wave 2, this estimate implies that having the wife earn more than the husband increases the likelihood of divorce by 50 percent. In Column (3), we including a control for relative income. The estimate decreases slightly to about 5 percentage points and becomes less significant ($p = 0.11$). Overall, our data suggests that departing from the traditional gender roles increases the likelihood of divorce.[42]

6 Home production and relative income

Traditional gender roles also contain prescriptions about the division of chores within the households. In this section, we explore whether, when the wife earns more than the husband, she or he adjusts her contribution to home production activities so as to alleviate the sense of gender-role reversal.

We use data from the ATUS/CPS, covering the years 2003 to 2011. As in the previous section, we restrict our analysis to couples where both the wife and the husband are between 18 and 65 years old and at least one person in the household has positive income. For each individual in the sample, we compute the total amount of time spent in non-market work and child care, measured in the number of hours per week. Following Aguiar and Hurst (2007), we define total number of hours spent in non-market work ($chores_i$) as the sum of time spent in "core" non-market work (which includes activities such as meal preparation and cleanup, doing laundry, ironing, dusting, vacuuming, and indoor household cleaning), time spent "obtaining goods and services" (such as grocery shopping) and time spent in "other" home production activities such as home maintenance, outdoor cleaning, vehicle repair, gardening, and pet care. We define total number of hours spent in child care ($childcare_i$) as the sum of time spent in primary child care (such as changing diapers and feeding the child), educational child care (such as helping a child with her homework) and recreational child care (such as playing games with children or taking them to the zoo). We define $totNonMarketWork_i$ as the sum $chores_i$ and $childcare_i$.

For each individual i in the sample, we define $lnWifeIncome_i$ and $lnHusbIncome_i$ and $lnTotIncome_i$ based on the weekly earnings reported in the CPS interviews. Based on these earn-

[42]Separation or divorce occurs when the marriage fully breaks down and can be regarded as the end-point of marital instability. Among couples that remain married in both survey waves, we can also examine whether $wifeEarnsMore$ in Wave 1 is associated with a deterioration in reported marital stability. We find some evidence that this is true (although most of the point estimates are not statistically significant). Conditional on Wave 1 responses, in marriages where the wife earns more than the husband, wives and husbands generally report (in Wave 2) that their marriages are less happy and that they have discussed separation. We do not find similar effects for the $marriageTrouble$ outcome (see Appendix Table 8).

ings we define $relativeIncome_i$ and $wifeEarnsMore_i$ as before. Summary statistics are presented in Appendix Table 9. Wives spend on average of 24.1 hours and 9.4 hours per week on chores and child care, respectively. For husbands, these numbers are 15.7 hours and 5.1 hours, respectively. Mean relative income is 0.34 and the wife earns more than the husband in 16 percent of the couples.

Ideally, we would like to compare the wife-husband gap in time spent on home production across couples where the wife earns more than the husband and those where she does not. Unfortunately, the ATUS/CPS only includes one respondent per household. Thus, to analyze how relative income impacts the division of home production, we will focus on the interaction between the impact of gender and the impact of relative income on time use. Specifically, in Column (1) of Panel (a) in Table 6, we consider the baseline OLS model:

$$\begin{aligned} totNonMarketWork_i \;=\; & \beta_0 + \beta_1 \times female_i \times wifeEarnsMore_i \\ & + \beta_2 \times female_i + \beta_3 \times wifeEarnsMore_i \\ & + \beta_4 \times lnWifeIncome_i + \beta_5 \times female_i \times lnWifeIncome_i \\ & + \beta_6 \times lnHusbIncome_i + \beta_7 \times female_i \times lnHusbIncome_i \\ & + \beta_8 \times lnTotIncome_i + \beta_9 \times female_i \times lnTotIncome_i \\ & + \beta_{10} \times X_i + \beta_{11} \times female_i \times X_i + \varepsilon_i \end{aligned}$$

where X_i includes year, state, and day of the week fixed effects, indicator variables for whether the wife is working, whether the husband is working, the wife and the husband's race and education groups, and a quadratic in the wife's and the husband's age. Our coefficient of interest is β_1. A positive estimate of β_1 would indicate that, *ceteris paribus*, in couples where the wife earns more than the husband, she also spends more hours doing non-market work and childcare. The estimate of β_1 is 1.36 ($p < 0.05$). In Column (2) we include more flexible cubic polynomial controls for the wife's and the husband's income. The estimate of β_1 is similar at 1.64 ($p < 0.05$). In Column (3) we include $relativeIncome_i$ as a control. The estimate of β_1 increases to 2.19 ($p < 0.01$). Thus, once again we see that relative income is particularly important if it implies a reversal in traditional gender roles.[43]

[43] One potential source of an omitted variable bias would be that in couples that are "more traditional," women are less likely to earn more than their husbands and are more likely to take on a larger share of housework. This force would bias the estimate of β_1 downwards, in the opposite direction of our finding.

In Column (4), we add, to the baseline specification, controls for the presence of children of different ages in the household. Specifically, we add indicator variables for whether there is no child, the youngest child is younger than 3, the youngest child is between 4 and 6 years of age, or the youngest child is older than 6. The estimate remains largely unchanged. Finally, our results are robust to restricting the sample to time-use during week-days only (Column (5)). In Panels (b) and (c) we consider the same specifications, but consider the two components of total non-market work, $chores_i$ and $childcare_i$, separately. The estimates suggest that most if not all of the effects on total non-market work are driven by chores rather than childcare.

In summary, our analysis of the time use data suggests that gender identity considerations may lead a woman who seems threatening to her husband because she earns more than he does to engage in a larger share of home production activities, particularly household chores. Akerlof and Kranton (2000) report that women do not undertake less than half of the housework even if they work or earn more than the husband. Our finding is even more striking; the (reverse) gender gap in non-market work is greater when the wife earns more than the husband.

7 Conclusion

The evidence presented in this paper is consistent with the view that gender identity norms, and in particular the norm that "a man should earn more than his wife," impact a wide range of social and economic outcomes. In particular, we argue that the prevalence of this norm helps explain the distribution of relative income within US households, the patterns of marriage, divorce and women's labor market participation, and the division of home production activities between husbands and wives.

By definition, the gender identity norm that we focus on in this paper would be of no relevance in a world where a woman could never earn more than her (potential or actual) husband. The relative gains in women's labor market opportunities over the last half century, however, have turned gender identity into an increasing relevant constraint, with real economic and social consequences. We suspect that the changes in women's relative income are particularly important because they happened quickly in comparison to the slow-moving social norms and concepts of gender.

While our empirical work focuses on the US, rapid gains in women's labor market opportunities are not unique to the US. Even more rapid changes have taken place in developed Asian countries, such as Korea and Japan. At the same time, these Asian countries have experienced large declines in marriage rates and fertility among educated women. As suggested by Hwang (2012), the interaction of economic growth and intergenerational transmission of gender attitudes might play an important part in these developments.

In future work, we would like to better understand the long-run determinants of gender identity. While the evidence in this paper suggests that the behavioral prescription that "a man should earn more than his wife" helps explain economic and social outcomes even in the most recent decade, this does not imply that this prescription is as strong today as it was in the past. How are gender identity norms evolving in the face of market forces that are making those norms more costly?

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Table 1: Marriage Rates and Relative Income

	Dependent variable: *MaleMarried*											
	Actual			Predicted			Bartik (1970)			Bartik (1980)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PrWomanEarnsMore	-0.181*	-0.307***	-0.192**	-0.214***	-0.200***	-0.199***	-0.438***	-0.317***	-0.234	-0.510***	-0.399***	-0.347**
	[0.101]	[0.081]	[0.078]	[0.060]	[0.049]	[0.051]	[0.118]	[0.106]	[0.156]	[0.097]	[0.095]	[0.142]
lnWomensIncome	0.046***	0.056***	0.051**	0.076***	0.055***	0.037	0.236***	0.110**	0.304	0.300***	0.153***	0.503***
	[0.014]	[0.013]	[0.022]	[0.016]	[0.014]	[0.041]	[0.040]	[0.050]	[0.233]	[0.044]	[0.053]	[0.171]
lnMensIncome	0.056*	0.086***	0.169***	0.000	0.051**	-0.012	0.061	0.182***	-0.363**	0.064*	0.199***	-0.299
	[0.030]	[0.024]	[0.042]	[0.029]	[0.021]	[0.064]	[0.038]	[0.045]	[0.151]	[0.038]	[0.048]	[0.215]
sexRatio		-0.038***	-0.041***		-0.036***	-0.036***		-0.018**	-0.011		-0.013*	-0.005
		[0.008]	[0.008]		[0.009]	[0.008]		[0.008]	[0.008]		[0.008]	[0.009]
femaleIncarcerationRate		-0.324	-0.249		-0.356	-0.330		-0.240	-0.181		-0.126	-0.113
		[0.213]	[0.208]		[0.216]	[0.209]		[0.198]	[0.183]		[0.190]	[0.177]
maleIncarcerationRate		0.425***	0.455***		0.217***	0.194***		0.193***	0.083		0.196**	0.103
		[0.076]	[0.084]		[0.068]	[0.064]		[0.071]	[0.081]		[0.075]	[0.075]
femaleAvgYearsOfEducation		0.007	0.007		0.004	0.004		0.004	-0.000		0.005	0.001
		[0.006]	[0.006]		[0.007]	[0.006]		[0.007]	[0.006]		[0.009]	[0.007]
maleAvgYearsOfEducation		-0.032***	-0.029***		-0.028***	-0.024***		-0.022**	-0.010		-0.024**	-0.014*
		[0.009]	[0.008]		[0.009]	[0.007]		[0.008]	[0.007]		[0.010]	[0.007]
numFemales		-0.000	-0.000		-0.000	0.000		-0.000	-0.000		-0.000	-0.000
		[0.000]	[0.000]		[0.000]	[0.000]		[0.000]	[0.000]		[0.000]	[0.000]
numMales		0.000	0.000		0.000	0.000		0.000*	0.000		0.000*	0.000**
		[0.000]	[0.000]		[0.000]	[0.000]		[0.000]	[0.000]		[0.000]	[0.000]
Observations	4,365	4,365	4,365	4,236	4,236	4,236	4,423	4,423	4,423	3,646	3,646	3,646
R-squared	0.989	0.990	0.990	0.988	0.989	0.990	0.989	0.989	0.990	0.990	0.990	0.991
Control for deciles of men's and women's income	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Note: Data is from 1970-2000 Censuses and 2010 ACS 3-year aggregate (2008-2010). Level of observation is marriage market by decade. All specifications include marriage market fixed effects, decade fixed effects, and the decade interacted with the age group, the education group, the race, and the state of residence. *PrWomanEarnsMore* is the probability that a randomly chosen woman earns more than a randomly chosen man. See text for further details. Regressions are weighted by the number of women in the marriage market. Standard errors clustered at the state level are in brackets. ***significant at 1%, **at 5%, *at 10%.

Table 2: Potential Relative Income and Wife's Labor Force Participation

Dependent variable:	*Wife in the labor force*											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PrWifeEarnsMore	-0.254***	-0.182***	-0.179***	-0.191***	-0.182***	-0.154***	-0.213***	-0.148***	-0.099***	-0.091***	-0.090***	-0.102***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.014]	[0.008]	[0.007]	[0.006]	[0.005]	[0.006]	[0.006]
Obs.	6564953	6564953	6564953	6564953	6564953	321298	1682558	1729726	1729171	1102200	991039	991039
R-squared	0.10	0.10	0.11	0.12	0.15	0.06	0.08	0.09	0.08	0.09	0.09	0.09
Additional controls:												
Cubic in *lnHusbIncome*	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
lnMedianWifePotential X lnHusbIncome	no	no	yes	yes	yes	no	no	no	no	no	no	no
anyChild(ren)	no	no	no	yes	yes	no	no	no	no	no	no	no
Wife's demographic group X Husband's demographic group	no	no	no	no	yes	no	no	no	no	no	no	no
PrWifeEarnsMoreAtMarriage	no	no	no	no	no	no	no	no	no	no	no	yes
Vigintiles of the wife's and the husband's potential income at marriage	no	no	no	no	no	no	no	no	no	no	no	yes
Sample restriction?	none	none	none	none	none	1970	1980	1990	2000	2010	2010^{sub}	2010^{sub}

Note: Data is from 1970-2000 Censuses and 2010 ACS 3-year aggregate (2008-2010). Sample consists of couples where both the wife and the husband are between 18 and 65 years old and the husband is working. Sample restriction 2010^{sub} indicates a subsample where the difference between year of marriage and the closest census year is no more than 5 years. *PrWifeEarnsMore* is the probability that wife's income would exceed the husband's if her income were drawn from the distribution of positive earnings in the wife's de *lnHusbIncome* is the log of husband's income. Variable *lnMedianWifePotential* is the log of the median of the distribution of positive earnings in the wife's demographic group. Variable *anyChild(ren)* is a binary variable that equals 1 if the wife reports having any child, 0 otherwise. Variable *PrWifeEarnsMoreAtMarriage* is the probability that income drawn from the distribution of positive earnings in the wife's demographic group exceeds income drawn from the distribution of positive earnings in the husband's demographic group in the closest census year to the year of their marriage. All regressions include controls for log of husband's income, vigintiles of the wife's potential income, wife's and husband's education (5 categories), wife's and husband's 5-year age group, wife's and husband's race, year and state fixed effects. ***significant at 1% level, **at 5%, *at 10%.

Table 3: Potential Relative Income and Wife's Realized Earnings

Dependent variable:	*incomeGap*											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PrWifeEarnsMore	-0.094***	-0.174***	-0.173***	-0.198***	-0.196***	-0.124***	-0.208***	-0.093***	-0.100***	-0.205***	-0.210***	-0.225***
	[0.006]	[0.007]	[0.007]	[0.007]	[0.007]	[0.021]	[0.012]	[0.011]	[0.010]	[0.011]	[0.012]	[0.012]
Obs.	4515564	4515564	4515564	4515564	4515564	164721	1033605	1240755	1274464	802019	721512	721512
R-squared	0.01	0.01	0.01	0.02	0.06	0	0	0.01	0.01	0.01	0.01	0.02
Additional controls:												
Cubic in *lnHusbIncome*	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
lnMedianWifePotential X lnHusbIncome	no	no	yes	yes	yes	no	no	no	no	no	no	no
any child(ren)	no	no	no	yes	yes	no	no	no	no	no	no	no
Wife's demographic group X Husband's demographic group	no	no	no	no	yes	no	no	no	no	no	no	no
PrWifeEarnsMoreAtMarriage	no	no	no	no	no	no	no	no	no	no	no	yes
husband's potential income at marriage	no	no	no	no	no	no	no	no	no	no	no	yes
Sample restriction?	none	none	none	none	none	1970	1980	1990	2000	2010	2010^{sub}	2010^{sub}

Note: Data is from 1970-2000 Censuses and 2010 ACS 3-year aggregate (2008-2010). Sample consists of couples where both the wife and the husband are between 18 and 65 years old and the husband is working. Variable *incomeGap* measures the difference between the wife's realized and potential earnings. *PrWifeEarnsMore* is the probability that wife's income would exceed the husband's if her income were drawn from the distribution of positive earnings in the wife's demographic group. Variable *lnHusbIncome* is the log of husband's income. Variable *lnMedianWifePotential* is the log of the median of the distribution of positive earnings in the wife's demographic group. Variable *anyChild(ren)* is a binary variable that equals 1 if the wife reports having any child, 0 otherwise. Variable *PrWifeEarnsMoreAtMarriage* is the probability that income drawn from the distribution of positive earnings in the wife's demographic group exceeds income drawn from the distribution of positive earnings in the husband's demographic group in the closest census year to the year of their marriage. Sample restriction 2010^{sub} indicates a subsample where the difference between year of marriage and the closest census year is no more than 5 years. All regressions include controls for log of husband's income, vigintiles of the wife's potential income, wife's and husband's education (5 categories), wife's and husband's 5-year age group, wife's and husband's race, year and state fixed effects. ***significant at 1% level, **at 5%, *at 10%.

Table 4: Relative Income and Marital Satisfaction

Respondent:	Wife			Husband			Both husband and wife		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel (a); Dependent variable: *happyMarriage*								
wifeEarnsMore	-0.071*	-0.077**	-0.058	-0.065*	-0.043	-0.081*	-0.068**	-0.060*	-0.070*
	[0.036]	[0.038]	[0.044]	[0.037]	[0.037]	[0.044]	[0.031]	[0.032]	[0.036]
Obs.	3,822	3,822	3,822	3,837	3,837	3,837	7,659	7,659	7,659
R-squared	0.026	0.027	0.026	0.040	0.041	0.040	0.025	0.026	0.025
	Panel (b); Dependent varible: *marriageTrouble*								
wifeEarnsMore	0.088**	0.074**	0.107***	0.076**	0.081**	0.052	0.082***	0.078***	0.079**
	[0.035]	[0.036]	[0.041]	[0.033]	[0.033]	[0.038]	[0.027]	[0.029]	[0.033]
Obs.	3,757	3,757	3,757	3,763	3,763	3,763	7,520	7,520	7,520
R-squared	0.049	0.050	0.049	0.046	0.047	0.047	0.047	0.048	0.047
	Panel (c); Dependent variable: *discussSeparation*								
wifeEarnsMore	0.084***	0.073**	0.073**	0.053**	0.054**	0.048	0.068***	0.064***	0.060**
	[0.028]	[0.029]	[0.033]	[0.026]	[0.026]	[0.030]	[0.024]	[0.024]	[0.028]
Obs.	3,742	3,742	3,742	3,765	3,765	3,765	7,507	7,507	7,507
R-squared	0.041	0.042	0.041	0.032	0.032	0.032	0.034	0.034	0.034
Additional controls:									
Cubic in *lnWifeIncome* and *lnHusbIncome*	no	yes	no	no	yes	no	no	yes	no
relativeIncome	no	no	yes	no	no	yes	no	no	yes

Note: The data is from Wave 1 of the National Survey of Family and Households (NSFH). Sample is restricted to couples where both the wife and the husband are between 18 and 65 years old and at least one person in the household has positive income. Variable *relativeIncome* is the share of the household income earned by the wife. Varible *wifeEarnsMore* is an indicator variable for whether *relativeIncome* > 0.5. Variables *lnWifeIncome* and *lnHusbIncome* are the logs of the wife's and husband's income, respectively. Variables *happyMarriage, marriageTrouble,* and *discussSeparation* are binary variables based on respondents' answers about their marriage (details are in the text). All regressions include log of the wife's income, log of the husband's income, log of the total household income, a quadratic in wife and husband's age, indicator variables for wife and husband's race and education (5 categories), region fixed effects, and an indicator variable for whether only the wife is working or only the husband is working. Regressions in Columns (7)-(9) include an indicator variable for whether the wife or the husband is the respondent and have standard errors clustered at the level of the couple. All regressions are weighted using the Wave 1 person weights from NSFH. Robust standard errors are reported in brackets. ***significant at 1%, **at 5%, *at 10%.

Table 5: Relative Income and Divorce

	Dependent varible: *divorced*		
	(1)	(2)	(3)
wifeEarnsMore	0.062**	0.060**	0.048
	[0.025]	[0.026]	[0.030]
Obs.	3,439	3,439	3,439
R-squared	0.080	0.086	0.080
Additional controls:			
Cubic in *lnWifeIncome* and *lnHusbIncome*	no	yes	no
relativeIncome	no	no	yes

Note: The data is from Waves 1 and 2 of the National Survey of Family and Households (NSFH). Sample is restricted to couples where both the wife and the husband are between 18 and 65 years old (in Wave 1) and at least one person in the household has positive income. Variable *relativeIncome* is the share of the household income earned by the wife. Variable *divorced* is an indicator for whether the couple is divorced or separated as of Wave 2. Varible *wifeEarnsMore* is an indicator variable for whether relativeIncome > 0.5. Variables *lnWifeIncome* and *lnHusbIncome* are the logs of the wife's and husband's income, respectively. All regressions include log of the wife's income, log of the husband's income, log of the total household income, a quadratic in wife and husband's age, indicator variables for wife and husband's race and education (5 categories), region fixed effects, and an indicator variable for whether only the wife is working or only the husband is working. All regressions are weighted using the Wave 1 person weights from NSFH. Robust standard errors are reported in brackets. ***significant at 1%, **at 5%, *at 10%.

Table 6: Relative Income and the Gender Gap in Non-Market Work and Childcare

	(1)	(2)	(3)	(4)	(5)
	Panel (a); Dependent variable: *totNonMarketWork*				
wifeEarnsMore	0.235	-0.150	0.307	-0.126	-0.177
	[0.472]	[0.495]	[0.589]	[0.481]	[0.634]
female X wifeEarnsMore	1.362**	1.643**	2.187***	1.827***	2.264**
	[0.685]	[0.710]	[0.847]	[0.690]	[0.914]
Obs.	45,074	45,074	45,074	45,074	22,377
R-squared	0.156	0.156	0.156	0.202	0.277
	Panel (b); Dependent variable: *chores*				
wifeEarnsMore	-0.006	-0.268	0.442	-0.284	-0.432
	[0.403]	[0.423]	[0.503]	[0.422]	[0.539]
female X wifeEarnsMore	1.186**	1.397**	1.466**	1.417**	2.029***
	[0.585]	[0.607]	[0.724]	[0.606]	[0.777]
Obs.	45,074	45,074	45,074	45,074	22,377
R-squared	0.095	0.096	0.095	0.098	0.154
	Panel (c); Dependent variable: *childcare*				
wifeEarnsMore	0.241	0.118	-0.135	0.159	0.255
	[0.233]	[0.244]	[0.291]	[0.221]	[0.308]
female X wifeEarnsMore	0.176	0.246	0.721*	0.410	0.235
	[0.338]	[0.351]	[0.418]	[0.317]	[0.444]
Obs.	45,074	45,074	45,074	45,074	22,377
R-squared	0.168	0.168	0.168	0.319	0.362
Additional controls					
Cubic in *lnWifeIncome* and *lnHusbIncome*	no	yes	no	yes	yes
relativeIncome	no	no	yes	no	no
children	no	no	no	yes	yes
Sample restriction	none	none	none	none	week-day only

Note: The data is from ATUS/CPS, 2003 to 2011. Sample is restricted to married individuals in the ATUS/CPS who are between 18 and 65 years old and whose spouse is also between 18 and 65 years old. We further restrict the sample to couples where at least one person in the household has positive income. Variable *chores* is the amount of time spent on non-market work (not including childcare). Variable *childcare* is the amount of time spent on childcare. Variable *totNonMarketWork* is the sum of *chores* and *childcare.* Variables *lnWifeIncome* and *lnHusbIncome* are the logs of the wife's and husband's income, respectively. Variable *relativeIncome* is the share of the household income earned by the wife. Varible *wifeEarnsMore* is an indicator variable for whether *relativeIncome* > 0.5. Variable *children* is an indicator variable for whether there is no child, the youngest child is younger than 3, the youngest child is between 4 and 6 years of age, or the youngest child is older than 6. All regressions include log of the wife's income, log of the husband's income, log of the total household income, year, state, and day of the week fixed effects, the wife and the husband's race, a quadratic in wife and husband's age, and indicator variables for the wife's and the husband's education groups, for whether only the husband is working, and for whether only the wife is working. Furthermore, we also include the interaction of all these controls with an indicator variable for whether the respondent is female. Each observation is weighted using the ATUS/CPS weight. ***significant at 1% level, **at 5%, *at 10%.

Appendix Table 1: Marriage Markets - Fraction of Wives Marrying Husbands in Particular Age, Education and Race Groups from 1970 to 2010

Age Groups

	Husband's Age			
Wife's Age	24 to 33	34 to 43	44 to 53	Other
22 to 31	75.6%	17.0%	1.5%	5.9%
32 to 41	13.0%	69.6%	15.6%	1.8%
42 to 51	0.6%	14.1%	68.2%	17.1%

Education Groups

	Husband's Education	
Wife's Education	High School or Less	Some College or More
High School or Less	73.4%	26.6%
Some College or More	23.7%	76.3%

Race Groups

	Husband's Race		
Wife's Race	White	Black	Hispanic
White	98.0%	0.4%	1.5%
Black	2.2%	96.9%	0.9%
Hispanic	17.1%	1.3%	81.6%

Note: Data from the 1970 to 2000 Censuses and the 2010 3-year ACS (2008 to 2010).

Appendix Table 2: Summary Statistics - Marriage Market Sample

	N	Mean	S.D.
All years			
PrWomanEarnsMore - Actual	4412	0.239	0.077
PrWomanEarnsMore - Predicted	4236	0.259	0.076
PrWomanEarnsMore - Bartik (1970)	4456	0.234	0.073
PrWomanEarnsMore - Bartik (1980)	3651	0.240	0.070
Male marriage rate	4423	0.660	0.142
Female marriage rate	4456	0.638	0.147
1970			
PrWomanEarnsMore - Actual	772	0.106	0.048
PrWomanEarnsMore - Predicted	670	0.140	0.058
PrWomanEarnsMore - Bartik (1970)	805	0.114	0.045
PrWomanEarnsMore - Bartik (1980)	-	-	-
Male marriage rate	777	0.826	0.070
Female marriage rate	805	0.792	0.092
1980			
PrWomanEarnsMore - Actual	907	0.170	0.061
PrWomanEarnsMore - Predicted	876	0.199	0.071
PrWomanEarnsMore - Bartik (1970)	910	0.166	0.061
PrWomanEarnsMore - Bartik (1980)	910	0.166	0.060
Male marriage rate	908	0.733	0.120
Female marriage rate	910	0.697	0.131
1990			
PrWomanEarnsMore - Actual	907	0.235	0.052
PrWomanEarnsMore - Predicted	889	0.257	0.063
PrWomanEarnsMore - Bartik (1970)	911	0.232	0.056
PrWomanEarnsMore - Bartik (1980)	911	0.232	0.055
Male marriage rate	911	0.662	0.134
Female marriage rate	911	0.644	0.132
2000			
PrWomanEarnsMore - Actual	915	0.276	0.053
PrWomanEarnsMore - Predicted	903	0.287	0.052
PrWomanEarnsMore - Bartik (1970)	916	0.265	0.044
PrWomanEarnsMore - Bartik (1980)	916	0.267	0.044
Male marriage rate	915	0.629	0.121
Female marriage rate	916	0.613	0.135
2010			
PrWomanEarnsMore - Actual	911	0.306	0.056
PrWomanEarnsMore - Predicted	898	0.320	0.051
PrWomanEarnsMore - Bartik (1970)	914	0.304	0.040
PrWomanEarnsMore - Bartik (1980)	914	0.306	0.040
Male marriage rate	912	0.573	0.149
Female marriage rate	914	0.559	0.157

Note: Data from the 1970 to 2000 Censuses and the 2010 3-year ACS (2008 to 2010). Each observation is a marriage market defined by the interaction of age-group*race*education-group*state. Variable *PrWomanEarnsMore* is the likelihood that a randomly chosen woman earns more than a randomly chosen man within a marriage market. "Actual" refers to the use of actual earnings to construct *PrWomanEarnsMore,* "Predicted" refers to the use of predicted earnings based on the woman or man's demographic group. "Bartik (1970)" refers to the use of 1970 industry shares and the national growth in industry wages to compute predicted earnings. "Bartik (1980)" refers to the use of 1980 industry shares and the national growth in industry wages to compute predicted earnings (this measure is not computed for 1970). See text for details.

Appendix Table 3: Change in PrWomanEarnsMore from 1970 to 2010 by Age Group

	Change in *PrWomanEarnsMore* from 1970 to 2010			
Age Group	No. of Marriage Markets	10th Percentile	Mean	90th Percentile
22 to 31 (F), 24 to 33 (M)	267	0.077	0.178	0.294
32 to 41 (F), 34 to 43 (M)	256	0.119	0.205	0.317
42 to 51 (F), 44 to 53 (M)	248	0.057	0.167	0.281

Note: Data from the 1970 to 2000 Censuses and the 2010 3-year ACS (2008 to 2010). Changes are calculated based on Actual income.

Appendix Table 4: First Stage Regressions of Moments of Predicted Male Income on Moments of 1970 Bartik

	Dependent variable: Selected Percentiles of Predicted *lnMensIncome*					
	Mean	10th	30th	50th	70th	90th
	(1)	(2)	(3)	(4)	(5)	(6)
Percentiles of 1970 Bartik *lnMensIncome:*						
Mean	0.706***					
	[0.070]					
10th		0.399***				
		[0.033]				
30th			0.531***			
			[0.078]			
50th				0.631***		
				[0.112]		
70th					0.925***	
					[0.086]	
90th						0.798***
						[0.073]
Observations	4,413	4,413	4,413	4,413	4,413	4,413
R-squared	0.995	0.971	0.981	0.981	0.988	0.990
	Dependent variable: Selected Percentiles of Predicted *lnWomensIncome*					
	Mean	10th	30th	50th	70th	90th
	(1)	(2)	(3)	(4)	(5)	(6)
Percentiles of 1970 Bartik *lnWomensIncome:*						
Mean	0.980***					
	[0.077]					
10th		0.393***				
		[0.044]				
30th			0.395***			
			[0.033]			
50th				0.874***		
				[0.083]		
70th					0.683***	
					[0.177]	
90th						1.077***
						[0.147]
Observations	4,375	4,375	4,375	4,375	4,375	4,375
R-squared	0.994	0.969	0.977	0.976	0.983	0.989

Note: Data is from 1970-2000 Censuses and 2010 ACS 3-year aggregate (2008-2010). Level of observation is marriage market by decade. All specifications include the same controls as Table 1 as well as marriage market fixed effects, decade fixed effects, and the decade interacted with the age group, the education group, the race, and the state of residence. See text for further details. Regressions are weighted by the number of women in the marriage market. Standard errors clustered at the state level are in brackets. ***significant at 1%, **at 5%, *at 10%.

Appendix Table 5: Summary Statistics - Married couples in the Census

	N	Mean	S.D.
All years			
PrWifeEarnsMore	6564953	0.18	0.25
wifeLFP	6564953	0.66	0.47
incomeGap	4515564	0.00	0.77
lnHoursWorked	4087444	3.52	0.44
1970			
PrWifeEarnsMore	321298	0.09	0.19
wifeLFP	321298	0.44	0.50
incomeGap	164721	0.00	0.74
lnHoursWorked	128397	3.46	0.48
1980			
PrWifeEarnsMore	1682558	0.12	0.22
wifeLFP	1682558	0.57	0.49
incomeGap	1033605	0.00	0.77
lnHoursWorked	877570	3.48	0.45
1990			
PrWifeEarnsMore	1729726	0.17	0.24
wifeLFP	1729726	0.70	0.46
incomeGap	1240755	0.00	0.76
lnHoursWorked	1126726	3.52	0.43
2000			
PrWifeEarnsMore	1729171	0.21	0.26
wifeLFP	1729171	0.72	0.45
incomeGap	1274464	0.00	0.78
lnHoursWorked	1181503	3.55	0.42
2010			
PrWifeEarnsMore	1102200	0.26	0.28
wifeLFP	1102200	0.74	0.44
incomeGap	802019	0.00	0.78
lnHoursWorked	773248	3.54	0.44

Note: Data from the 1970 to 2000 Censuses and the 2010 3-year ACS (2008 to 2010). Sample consists of couples where both the wife and the husband are between 18 and 65 years old and the husband is working. *PrWifeEarnsMore* is the probability that wife's income would exceed the husband's if her income were drawn from the distribution of positive earnings in the wife's demographic group. Variable *wifeLFP* is an indicator variable for whether the wife is in the labor force. Variable *incomeGap* measures the difference between the wife's realized and potential earnings. Variable *lnHoursWorked* indicates the logarithm of the total number of hours the wife was at work during the previous week.

Appendix Table 6: Relative Income, Wife's Working Hours and Wife's Realized Earnings

Dependent variable:	*lnHoursWorked*		*incomeGap*			
	(1)	(2)	(3)	(4)	(5)	(6)
PrWifeEarnsMore	-0.066	-0.061	-0.152	-0.157	-0.103	-0.112
	[0.004]**	[0.003]**	[0.008]**	[0.008]**	[0.007]**	[0.007]**
Obs.	3904512	3904512	3904512	3904512	3904512	3904512
R-squared	0.05	0.09	0.02	0.07	0.18	0.22
Additional controls:						
Cubic in *lnHusbIncome*	yes	yes	yes	yes	yes	yes
lnMedianWifePotential X lnHusbIncome	yes	yes	yes	yes	yes	yes
anyChild(ren)	yes	yes	yes	yes	yes	yes
Wife's demographic group X Husband's demographic group	no	yes	no	yes	no	yes
ln(hoursworked)	no	no	no	no	yes	yes

Note: Data is from 1970-2000 Censuses and 2010 ACS 3-year aggregate (2008-2010). Sample consists of couples where both the wife and the husband are between 18 and 65 years old and the husband is working. Variable *incomeGap* measures the difference between the wife's realized and potential earnings. Variable *lnHoursWorked* is the logarithm of the total number of hours the wife was at work during the previous week. *PrWifeEarnsMore* is the probability that wife's income would exceed the husband's if her income were drawn from the distribution of positive earnings in the wife's demographic group. Variable *lnHusbIncome* is the log of husband's income. Variable *lnMedianWifePotential* is the log of the median of the distribution of positive earnings in the wife's demographic group. Variable *anyChild(ren)* is a binary variable that equals 1 if the wife reports having any child, 0 otherwise. Variable *PrWifeEarnsMoreAtMarriage* is the probability that income drawn from the distribution of positive earnings in the wife's demographic group exceeds income drawn from the distribution of positive earnings in the husband's demographic group in the closest census year to the year of their marriage. Sample is restricted to observations where *lnHoursWorked* is non-missing. All regressions include controls for log of husband's income, vigintiles of the wife's potential income, wife's and husband's education (5 categories), wife's and husband's 5-year age group, wife's and husband's race, year and state fixed effects. ***significant at 1% level, **at 5%, *at 10%.

Appendix Table 7: Summary Statistics - National Survey of Families and Households (NSFH)

	Wave 1			Wave 2		
	N	Mean	SD	N	Mean	SD
Wife's Responses:						
happyMarriage	3909	0.48	0.50	2720	0.43	0.49
marriageTrouble	3840	0.27	0.44	2863	0.25	0.43
discussSeparation	3825	0.14	0.35	2857	0.11	0.32
Husband's Responses:						
happyMarriage	3920	0.47	0.50	2568	0.40	0.49
marriageTrouble	3834	0.22	0.41	2711	0.20	0.40
discussSeparation	3836	0.12	0.32	2719	0.09	0.29
Couple's Characteristics:						
relativeIncome	4037	0.27	0.27			
wifeEarnsMore	4037	0.15	0.36			
divorced	3514	0.12	0.33			

Note: The data is from Waves 1 and 2 of the National Survey of Family and Households (NSFH). Sample is restricted to couples where both the wife and the husband are between 18 and 65 years old and at least one person in the household has positive income. The sample in Wave 2 is restricted to couples who are married in both Wave 1 and Wave 2. Variables *happyMarriage, marriageTrouble,* and *discussSeparation* are binary variables based on respondents' answers about their marriage (details are in the text). Variable *relativeIncome* is the share of the household income earned by the wife. Variable *wifeEarnsMore* is a binary variable that indicates whether *relativeIncome* > 0.5. Variable *divorced* indicates whether the couple is separated or divorced when they are re-interviewed in Wave 2.

Appendix Table 8: Relative Income and the Evolution of Marital Satisfaction

Respondent:	Wife		Husband		Both wife and husband	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel (a); Dependent variable: *happyMarriage*					
wifeEarnsMore	-0.084**	-0.116**	0.015	0.031	-0.033	-0.042
	[0.040]	[0.045]	[0.044]	[0.049]	[0.032]	[0.035]
Wave 1 Response	0.382***	0.383***	0.349***	0.349***	0.370***	0.370***
	[0.021]	[0.021]	[0.021]	[0.021]	[0.015]	[0.015]
Obs.	2,587	2,587	2,462	2,462	5,049	5,049
R-squared	0.188	0.186	0.188	0.188	0.180	0.179
	Panel (b); Dependent varible: *marriageTrouble*					
wifeEarnsMore	-0.010	-0.044	0.042	0.036	0.014	-0.005
	[0.036]	[0.042]	[0.037]	[0.041]	[0.029]	[0.033]
Wave 1 Response	0.292***	0.293***	0.272***	0.272***	0.283***	0.283***
	[0.024]	[0.024]	[0.025]	[0.025]	[0.019]	[0.019]
Obs.	2,672	2,672	2,547	2,547	5,219	5,219
R-squared	0.142	0.139	0.132	0.131	0.134	0.133
	Panel (c); Dependent variable: *discussSeparation*					
wifeEarnsMore	0.045*	0.034	0.045*	0.031	0.044**	0.033
	[0.025]	[0.029]	[0.025]	[0.029]	[0.021]	[0.024]
Wave 1 Response	0.281***	0.282***	0.242***	0.243***	0.265***	0.266***
	[0.030]	[0.030]	[0.032]	[0.032]	[0.024]	[0.024]
Obs.	2,655	2,655	2,557	2,557	5,212	5,212
R-squared	0.130	0.126	0.091	0.090	0.108	0.106
Additional controls:						
Cubic in *lnWifeIncome* and *lnHusbIncome*	yes	yes	yes	yes	yes	yes
relativeIncome	no	yes	no	yes	no	yes

Note: The data is from Waves 1 and 2 of the National Survey of Family and Households (NSFH). Sample is restricted to couples where both the wife and the husband are between 18 and 65 years old and at least one person in the household has positive income. Variable relativeIncome is the share of the household income earned by the wife. Varible wifeEarnsMore is an indicator variable for whether relativeIncome > 0.5. Variables lnWifeIncome and lnHusbIncome are the logs of the wife's and husband's income, respectively. Variables happyMarriage, marriageTrouble, and discussSeparation are binary variables based on respondents' answers about their marriage (details are in the text). All regressions include log of the wife's income, log of the husband's income, log of the total household income, a quadratic in wife and husband's age, indicator variables for wife and husband's race and education (5 categories), region fixed effects, and an indicator variable for whether only the wife is working or only the husband is working. Regressions in Columns (5) and (6) include an indicator variable for whether the wife or the husband is the respondent and have standard errors clustered at the level of the couple. All regressions are weighted using the Wave 1 person weights from NSFH. Robust standard errors are reported in brackets. ***significant at 1%, **at 5%, *at 10%.

Appendix Table 9: Summary Statistics - ATUS/CPS (2003-2011)

	N	Mean	S.D.
Wife's time use (hours per week)			
chores	23386	24.11	19.59
childcare	23386	9.41	13.93
totNonMarketWork	23386	33.52	24.21
Husband's time use (hours per week)			
chores	21688	15.66	18.38
childcare	21688	5.07	10.3
totNonMarketWork	21688	20.74	21.11
Income			
wifeIncome	45074	498.57	537.41
husbIncome	45074	985.66	707.25
relativeIncome	45074	0.34	0.31
wifeEarnsMore	45074	0.16	0.36

Note: The data is from ATUS/CPS, 2003 to 2011. Sample is restricted to married individuals in the ATUS/CPS who are between 18 and 65 years old and whose spouse is also between 18 and 65 years old. We further restrict the sample to couples where at least one person in the household has positive income. Variable *chores* is the amount of time spent on non-market work (not including childcare). Variable *childcare* is the amount of time spent on childcare. Variable *totNonMarketWork* is the sum of *chores* and *childcare*. Variables *wifeIncome* and *husbIncome* are the wife's and the husband's weekly income, respectively. Variable *relativeIncome* is the share of the household income earned by the wife. Varible *wifeEarnsMore* is an indicator variable for whether *relativeIncome* > 0.5.