

# Dondena Working Papers

Carlo F. Dondena Centre for Research  
on Social Dynamics and Public Policy

## **The Cost of Gender Identity Norms: Evidence from a Spouse Tax Credit**

T. Giommoni  
E. Rubolino

**Working Paper No. 153**  
July 2022

**Università Bocconi • The Dondena Centre**

Via Guglielmo Röntgen 1, 20136 Milan, Italy  
<http://www.dondena.unibocconi.it>

*The opinions expressed in this working paper are those of the author and not those of the Dondena Centre, which does not take an institutional policy position. © Copyright is retained by the author.*  
ISSN-2035-2034

# The Cost of Gender Identity Norms: Evidence from a Spouse Tax Credit\*

Tommaso Giommoni<sup>1</sup> and Enrico Rubolino<sup>2</sup>

<sup>1</sup>ETH Zurich

<sup>2</sup>University of Lausanne

July 26, 2022

## Abstract

The standard model of household behavior predicts that couples cooperate to maximize family income. This paper shows that gender identity norms represent an important friction preventing family income maximization. For identification, we focus on an Italian policy that grants a large tax credit to the main earner in a couple when the second earner reports income below a cutoff. Using new tax returns data, we show large bunching responses at the tax credit cutoff from second earner women, but no response from second earner men. This result suggests that household decisions are not Pareto-efficient when men are the second earner within the couple. Gender differences in bunching mostly emerge after marriage and childbirth, and do not reflect any gender-specific difference in scope for bunching. In support of the view that gender norms drive our results, we find that gender differences in bunching are relatively larger among immigrants coming from more conservative societies, and natives living in more gender-traditional municipalities. Additionally, these results have important implications for gender inequality: we show that the spouse tax credit persistently limits women's careers and amplifies the gender income gap.

**JEL codes:** H24; H31; J16.

**Keywords:** gender norms; gender inequality; spouse tax credit; income taxation.

---

\*We thank Sonia Bhalotra, Marius Brühlhart, Marko Köthenbürger and seminar participants at the University of Essex for comments.

Tommaso Giommoni: ETH Zurich, Department of Management, Technology, and Economics, Leonhardstrasse 21, 8092 Zurich, Switzerland; E-mail: [giommoni@ethz.ch](mailto:giommoni@ethz.ch); +41 44 632 29 25; Enrico Rubolino: University of Lausanne, Faculty of Business and Economics, Quartier de Chambronne, Internef 261, 1015 Lausanne, Switzerland; [enrico.rubolino@unil.ch](mailto:enrico.rubolino@unil.ch); +41 21 692 34 84.

# 1 Introduction

The standard model of household behavior states that individuals maximize a single household utility under a budget constraint (see, e.g., [Chiappori 1988](#); [Chiappori 1992](#); [Apps and Rees 1996](#); [Blundell et al. 2007](#)). In this model, spouses care about their family welfare, over and above their own well-being. Taken literally, the model predicts that the distribution of income within the couple would not matter: spouses cooperate to maximize the family income and household resources are allocated in the most economically efficient manner. This paper shows that gender identity norms represent an important friction preventing family income maximization. We provide empirical evidence that household income maximization choices are not Pareto-efficient when men are the second earner within the couple.

For identification, we take advantage of the Italian spouse tax credit: the main earner in a couple receives a large tax credit if the second earner reports gross annual income below 2,840.51 euros. The size of the tax credit is a negative function of the main earner's gross income. For main earners reporting less than 15,000 euros, the tax credit accounts, on average, for more than 40 percent of their tax burden (that is around one-tenth of their gross income). The tax credit then linearly decreases with income, and it is eventually phased out for main earners reporting more than 80,000 euros. The policy thus offers a large tax break to low- and middle-income families. Over the last decade, we observe that more than one-third of Italian families received the spouse tax credit.

The spouse tax credit offers a propitious testing ground for evaluating the standard model of household behavior. Since the Italian tax system is individually assessed, the policy creates a substantial "notch" in the budget constraint of families: a discontinuity in the choice set of second earner gross income versus family net income.<sup>1</sup> Under the standard model, the tax notch should induce second earners, who would otherwise report more income, to "bunch" right at the tax credit cutoff. By contrast, in a world where gender identity norms matter, the decision to bunch would be the result of a cost-benefit analysis, where the benefit of having larger family net income would be discounted by the cost of violating the adopted gender norm.<sup>2</sup> For instance, in couples that embrace the male breadwinner model - where

---

<sup>1</sup>A *notch* is defined as a discrete change in the *level* of the choice set. The spouse tax credit creates a tax notch because an incremental change in second earner income causes a discrete reduction in the level of main earner (and family) net tax liability. [Kleven and Waseem \(2013\)](#) develop a bunching approach based on notch points. Another type of bunching approach rests on *kink* points, where a discrete change is observed in the *slope* of the choice set ([Saez 2010](#); [Chetty et al. 2011](#)).

<sup>2</sup>Gender identity norms prescribe how men and women should behave (see the seminal contributions by [Akerlof and Kranton 2000](#) and [Akerlof and Kranton 2010](#)). Departures from the set of prescriptions defining the gender identity norm, such as who should be the main earner in the couple, would generate psychological costs and affect choices. [Bertrand et al. \(2015\)](#) provide a notable example of the non-monetary costs associated with violating gender identity norms: couples where the wife

wives are mostly out of the labor force or enter in the labor market as second earners -, men would adopt behaviors that allow them to “fill the gap” when the male breadwinner model fails. In this setting, gender norms may induce two important side effects. First, second earner men would be dissuaded from reporting income below the tax credit cutoff, differently from second earner women. Second, frequent bunching responses from second earner women might be associated with detrimental long-lasting effects on their careers. Therefore, in the presence of traditional gender norms, the spouse tax credit can create important economic inefficiencies and negative impacts on gender income inequalities.

Building on this idea, we combine novel tax returns data with a bunching approach (Kleven 2016). Our results provide striking evidence that gender identity norms shape individual behavior in reporting income.<sup>3</sup> We find sizable bunching at the tax credit cutoff from second earner women, but no response from second earner men. There is excess bunching below the tax notch by around 1.2 times the height of the counterfactual female income distribution, suggesting that the density of second earner women located in an income range strictly below the tax credit cutoff is 1.2 times larger than the density that we would have observed in the absence of the policy.<sup>4</sup> Our bunching estimate suggests that the female marginal buncher reduces her income by about 186 euros to let her husband enjoy a tax credit of nearly 689 euros, thus increasing family net income by around 503 euros. The absence of any bunching response from second earner men suggests that, *ceteris paribus*, couples where the husband is the second earner hold around 503 euros less than comparable couples where the wife is the second earner. For the representative family in our sample, this income loss corresponds to around 2.7 percent of the annual net family income.

We then examine whether gender differences in bunching response emerge with marriage. In family specialization models à la Becker (1991), married men mostly focus on working, while their wives are responsible for non-market production. If marriage “activates” gender identity norms, gender differences in bunching rate would thus emerge just after marriage. Using an event study approach, we show that gender differences in bunching rate appear right after marriage. By contrast, we find no significant difference before marriage, suggesting that pre-existing factors determining tax credit eligibility do not affect the formation of couples. We also find

---

outearns the husband are more likely to divorce and to report lower marriage satisfaction in survey.  
<sup>3</sup>Following the modern public economics literature (Saez et al. 2012), we focus on taxable income responses, which incorporate both real effects, such as labor supply responses, and tax evasion or tax avoidance responses.

<sup>4</sup>We flexibly control for the distribution of men’s income and the distribution of women’s income. Hence, we are not simply picking up the fact that women are more likely to report income close to the tax credit cutoff.

that gender differences in bunching response emerge after childbirth, thus suggesting that the spouse tax credit strengthens child penalties (Kleven et al. 2019a; Kleven et al. 2019b; Casarico and Lattanzio 2021).

Because women and men may sort into different occupations, one concern is that our finding reflects structural differences by gender in scope for bunching responses. For instance, women can sort into occupations that allow them more flexibility in adjusting their labor supply (see, e.g., Goldin and Katz 2011; Goldin 2014; Olivetti and Petrongolo 2016; Benny et al. 2021). To assuage these concerns, we investigate whether gender differences in bunching emerge at other points of the income distribution where a marginal tax rate change affects the choice set of *own* gross versus net income. We find no evidence of different responses by gender at these other discontinuities in the budget constraint. This result rules out the possibility that our main finding would simply reflect gender differences in scope for bunching (either for evasion or labor supply reasons).

To analyze whether gender norms are responsible for our results, we present two additional results. First, we conduct an epidemiological study of gender norms based on foreign-born immigrants.<sup>5</sup> Adjusting for selection in their current municipality of residence, we show that gender differences in bunching rate are relatively larger among immigrants coming from countries with more traditional gender norms. For instance, gender differences in bunching are much larger among immigrants born in places with lower female employment, such as Iraq or Saudi Arabia, than in places with higher female employment, such as China. Second, we find larger bunching differences in more gender-traditional municipalities, identified as those i) that were less likely to support the deregulation of abortion in a 1981 referendum; ii) where fewer female politicians are elected; iii) located in rural areas. At the individual level, we detect stronger responses among older women, that tend to report more conservative views on questions about gender norms in survey data.

In the final part of the paper, we study whether the spouse tax credit has any impact on secondary earners' career and gender inequalities. Although the economic rationale of the spouse tax credit is to offer insurance against labor market shocks, the policy can *persistently* affect the work (or income reporting) incentives of second earners. We assess gender differences in bunching hysteresis: how the probability of reporting income below the spouse tax credit cutoff evolves over time by second earners' gender. Focusing on the first individual-specific bunching episode observed in the data, we find that the probability of bunching in the successive year is around 17 percentage points larger for women with respect to men (41 versus 24 percent, respectively). This gender difference survives for many years: after 7 years since the

---

<sup>5</sup>See Fernández (2011) for a review on the epidemiological approach to study the role of cultural factors in economics.

first bunching episode, there is still a significant 20 percent probability of a bunching response from women, while the corresponding probability for men is not significantly different from zero.

We then show that our results have important implications for gender income gaps. We find that gross incomes of married women are 4 log points lower than those of married men at the first income decile, that is where the spouse tax credit strikes. Significant gender gaps do not emerge at other income deciles, with the notable exception of the top decile. In support of the argument that the spouse tax credit tends to fuel gender inequalities, we show that the gender gap in the bottom income decile is relatively smaller, if any, among unmarried individuals, where the spouse tax credit does not matter by definition. Although we cannot rule out alternative explanations for the emergence of a gender gap at this point of the income distribution (e.g., self-selection into married status by low-income women), this result seems to suggest that the spouse tax credit significantly contributes to gender income inequalities.

Finally, building from studies showing that gender norms significantly affect marital stability ([Bertrand et al. 2015](#); [Folke and Rickne 2020](#)), we show that bunching responses at the spouse tax credit cutoff are associated with a lower divorce rate. On average, we find that the probability of divorce is 1.3 percentage points (20 percent) lower among female second earners located barely below the spouse tax credit cutoff, relative to those barely above. We show similar effects, although of smaller magnitude, for male second earners. This result implies that gender identity norms are associated with both monetary and non-monetary costs. We further offer survey evidence that the violation of the male breadwinner model entails psychological costs for men, and both life and marriage dissatisfaction among women.

This paper contributes to three main literatures. First, our results show that cultural factors, such as gender identity norms, significantly shape individual behavior. This is consistent with the seminal contribution from [Akerlof and Kranton \(2000\)](#) and [Akerlof and Kranton \(2010\)](#), and it is in line with a growing literature showing that culture affects economic outcomes (see, e.g., [Fernández et al. 2004](#); [Guiso et al. 2006](#); [Fernández 2007](#); [Fernández and Fogli 2009](#); [Alesina et al. 2013](#); [Giuliano 2022](#)). Our analysis complements previous work on the impacts of gender identity norms. Previous studies have focused on divorce rate and couples' satisfaction ([Bertrand et al. 2015](#)), childcare allocation ([Ichino et al. 2021](#)), labor market choices following a spouse's layoff ([Halla et al. 2020](#)), stock market participation ([Ke 2021](#)), and misreporting income information in survey ([Roth and Slotwinski 2021](#)). Our analysis focuses on a novel, perhaps more compelling, outcome: adopting behaviors that maximize family income. To our knowledge, we also offer the first evidence of monetary costs that couples face when men are secondary earners.

Second, we contribute on a growing literature documenting that optimization frictions dampen responses to tax policy (Chetty et al. 2011; Chetty 2012; Kleven and Waseem 2013; Gelber et al. 2020). The existing literature has presented several sources of frictions, including imperfect knowledge (Chetty et al. 2013a), search costs and hours constraints (Chetty et al. 2011), cognitive ability (Bastani and Waldenström 2021), complexity (Bhargava and Manoli 2015), salience (Chetty et al. 2009), and rational inattention (Taubinsky and Rees-Jones 2018). We propose a new source of friction: gender identity norms. Incorporating these sources of optimization frictions into optimal tax models can help to reconcile some long-standing empirical puzzles in public economics, such as the divergence between micro and macro elasticity estimates (Chetty et al. 2013b). Our results should be taken into account in the design of a more efficient and equitable tax system.<sup>6</sup>

Finally, our results emphasize how policy-making can backfire in presence of traditional gender norms. By incentivizing second earner women to report income below a (small) income threshold, we show that a spouse tax credit limits women's income and creates a gender income gap. This result relates with studies showing how public policies can hold back female employment. In most countries, taxes and benefits depend on one's marital status and tend to reduce the labor supply of the secondary earner. Guner et al. (2012) show that switching to a tax system in which married individuals can file taxes separately would substantially increase female labor participation. More recently, Borella et al. (2022) show that eliminating marriage-related provisions in the US would significantly increase married women's labor market participation.

The rest of the paper proceeds as follows. In section 2, we describe the background and data. Section 3 illustrates a conceptual framework that helps to contextualize our findings and presents our empirical approach. Section 4 shows our main result: gender differences in bunching responses at the tax credit cutoff. Section 5 shows that this result is particularly concentrated in contexts with more traditional gender norms. In section 6, we discuss the implications of our findings for second earners' career, gender income inequality, and marital stability. Finally, section 7 concludes.

---

<sup>6</sup>Differentiating income tax rates by gender could be a solution to internalize the costs associated with gender identity norms. The implications of gender-based taxation have been studied by Alesina et al. (2011). Using a collective household model in which labor supply elasticities arise endogenously, they find that the optimal tax scheme would present higher marginal tax rates on men when gender-specific lump sum transfers are available. Empirical evidence on the labor market impacts from gender-based taxes has been recently studied by Rubolino (2022). Exploiting a recent policy change in Italy, he shows that lower payroll taxes on female hires stimulated female employment.

## 2 Institutional Background and Data

### 2.1 Gender Norms in Italy

Similarly to other Southern-European countries, Italy is a conservative society with traditional gender norms. The vast majority of families embraces the male breadwinner model, where wives are mostly out of the labor force or enter in the labor market as second earners. According to the [OECD Family Database](#), Italy ranks in lowest position regarding female labor market outcomes: in 2018, the full-time equivalent employment share of women was 40.3 percent, and the gender employment gap was 26.5 percentage points. In terms of gender pay differences, Italy looks relatively better: the gender gap in median earnings of full-time employees was around 5 percent in 2018 (OECD average is around 13 percent). [Casarico and Lattanzio \(2019\)](#) show that the gender pay gap declined steadily over the last two decades in Italy.

Using data that we will describe below, panel A of [Figure A1](#) shows trends in the share of couples where the wife is the main earner, divided by macro-region. We find that, on average, women are the head of the household in less than 10 percent of couples. The figure also shows that there are wide geographical differences: in 2020, a wife outearns her husband in around 15 percent of families living in the Northern Italy, while this happened in only 7 percent of couples from Southern Italy. The share of couples where the woman is the main earner has been steadily growing: it increased of around 5 percentage points (from 6 to 11 percent) over the 2013-2020 period.<sup>7</sup> Panel B in the figure shows that geographical differences in who leads the household are strongly correlated with measures of gender norms, such as the share of respondents agreeing that “men should have more right to a job than women” from the 2017 European Values Study.

The Italian society is also characterized by strong imbalances in family chores allocation. According to a nationwide survey conducted by the Italian Institute of Statistics (ISTAT) (see *Indagine sulle discriminazioni in base al genere, all'orientamento sessuale, all'appartenenza etnica*), more than one-fifth of married working women report “to feel overwhelmed by family chores.”<sup>8</sup> The survey also reveals other interesting facts about the Italian society. For example, around one-third of working women agrees or strongly agrees that “husbands are the main responsible for the provision

---

<sup>7</sup>This pattern emerges in virtually all of the developed world, following the observed increase in women’s labor force participation and education levels over the last decades. For example, among families in which both members received earnings, the share of families where the wife outearns the husband has increased from 15.9 to 29.3 percent in the U.S. between 1981 and 2015 ([Blau and Kahn 2017](#)). Furthermore, it seems that in the vast majority of couples where the wife is the main earner, this disparity tends to be persistent ([Winkler et al. 2005](#)).

<sup>8</sup>[Alesina and Ichino \(2009\)](#) discuss the implications of unpaid family work for labor supply decision of Italian women.

of family needs". These figures portray Italy as a gender-conservative environment, with considerable gender inequalities in many social and economic aspects. It thus provides a useful setting to study whether gender identity norms affect economic outcomes.

## 2.2 Spouse Tax Credit and Income Taxation in Italy

All Italian residents are subject to personal income taxation (IRPEF, *Imposta sul Reddito delle Persone Fisiche*). The tax base depends on individual income, computed by subtracting deductions from gross income. All sources of income, such as labor (including self-employed work), business and capital income enter the tax base. The tax schedule is progressive: it is composed of five income brackets with tax rates ranging from 23 to 43 percent (see [Table A1](#)). Tax rates and income bracket cutoffs have not been modified over the period we study.

The final tax burden is calculated net of tax credits. The Italian personal income tax system provides a wide array of tax credits. A spouse tax credit was introduced by law 917/1986 (see *Decreto del Presidente Della Repubblica*, 22 December 1986, n. 917, article 12). This policy grants the main earner in a couple to receive a tax credit if the second earner reports gross annual income below 2,840.51 euros.<sup>9</sup> Entitlement is also allowed for second earners that are out of the labor force. Spouse tax credit eligibility is self-reported by the main earner when filling tax returns. In the case of third-party reported earnings, workers can apply for receiving the tax credit directly from the [Italian Social Security Institute \(INPS\) website](#).

[Table 1](#) illustrates the main features of the spouse tax credit. The table reports the size of the tax credit (column 2), how much of the main earner's final tax burden is reduced thanks to the spouse the tax credit (column 3), and the importance of the tax credit in proportion to main earner's gross income (column 4). The tax credit is computed by a simple formula for main earners reporting income below 15,000 euros or between 40,000 and 80,000 euros, while it is a fixed amount for other income groups. Consistent with the main goal of compensating disadvantaged families, the tax credit is eventually phased out for main earners reporting more than 80,000 euros. The table shows that the size of the tax credit is a negative function of the main earner's gross income. For instance, a main earner with income lower than 10,000 euros would get a tax credit of 726.7 euros, that would almost halve her tax burden. On average, main earners with less than 15,000 euros get a tax credit that accounts for 43.2 percent of their tax burden, which corresponds to around 10 percent of their

---

<sup>9</sup>During the period Italy had its own currency, the cutoff was 3 million lire. It was then converted to 2,840.51 euros. A similar policy was also in place during the early post-war period, but based on different criteria (see *Decreto del Presidente Della Repubblica*, 29 January 1958, n. 645; *Supplemento Ordinario alla Gazzetta Ufficiale della Repubblica Italiana*, 7 July 1958, n. 162).

gross income. The relevance of the tax credit then monotonically decreases over the main earner’s income distribution, accounting for less than one-tenth of the tax burden for incomes above 29,000 euros.

Table 1: The Spouse Tax Credit

Main earner’s gross income (euros) (1)	Tax credit (euros) (2)	Tax credit (% of tax burden) (3)	Tax credit (% of gross income) (4)
-15,000	$800 - (110 * \text{gross income} / 15,000)$	43.2%	9.9%
15,001-29,000	690	12.9%	3.1%
29,001-29,200	700	9.5%	2.4%
29,201-34,700	710	8.4%	2.2%
34,701-35,000	720	7.5%	2.1%
35,001-35,100	710	7.4%	2.0%
35,101-35,200	700	7.2%	1.9%
35,201-40,000	690	6.5%	1.8%
40,001-80,000	$690 * [(80,000 - \text{gross income}) / 40,000]$	1.8%	0.6%
80,001-	0	0	0

*Note:* This table illustrates the main features of the spouse tax credit (law 917/1986). The main earner in a couple is eligible to claim a spouse tax credit if her spouse reports gross income below 2,840.51 euros. Column 2 shows the tax credit amount as a function of main earners’ annual gross income. Column 3 displays how much of the main earner’s final tax burden is reduced thanks to the spouse tax credit. The tax burden is calculated by applying the personal income tax schedule (see [Table A1](#)) at an income level equal to the median income in each main earner’s gross income group. Column 4 calculates the spouse tax credit as a share of main earner’s gross income, computed at the median income level of the corresponding main earner’s gross income bracket.

### 2.3 Data and Descriptive Evidence

We use administrative data provided by the Veneto tax administration, based on the universe of personal income tax returns for residents in the Veneto region. Veneto is an important and large Italian region: in 2020 it was the third richest region in Italy ([ISTAT](#)) and the fifth most populous ([ISTAT](#)).<sup>10</sup> As income taxes in Italy are filled individually, the unit of observation is the individual. The dataset contains taxable income data (divided in income sources) and basic socio-demographic characteristics, such as gender, marital status, date of birth, municipality of residence and nationality. We also observe all sources of tax deductions and credits. Data are available over the 2007-2014 period.

The main advantage of using tax returns data is that they provide information about the exact location of taxpayers over the income distribution. Moreover, in

<sup>10</sup>In Appendix [Figure A2](#), we show that Veneto scores slightly below the Italian average on traditional gender norms index, while Veneto’s female employment is relatively higher than the Italian average. Therefore, our estimates should provide a lower bound effect on the economic impacts of gender identity norms for the Italian society.

contrast to survey data, tax returns data have almost no measurement error. These administrative data are thus suitable for our empirical analysis, which consists in estimating whether the spouse tax credit affects income reporting behavior. Following standard practice in the literature, our bunching analysis focuses on self-employees.<sup>11</sup> Since income is self-reported, self-employees can adjust their taxable income for tax-related reasons. By contrast, since employees' wages are third-party reported, employees have limited room for adjusting their income and thus respond to the tax credit cutoff. We will confirm this stylized fact below.

### 2.3.1 Descriptive Evidence

[Table A2](#) reports the summary statistics on our sample of self-employees, which includes around 2.7 million taxpayers. Panel A of [Table A2](#) focuses on male taxpayers, who represent the 69.7 percent of the sample: the average gross declared income is 34,695 euros and the 18.7 percent of them receive the spouse tax credit. Panel B of [Table A2](#) shows the summary statistics for the sample of female taxpayers: the average gross reported income is 25,049 euros and the fraction of spouse tax credit's recipients is 2 percent.

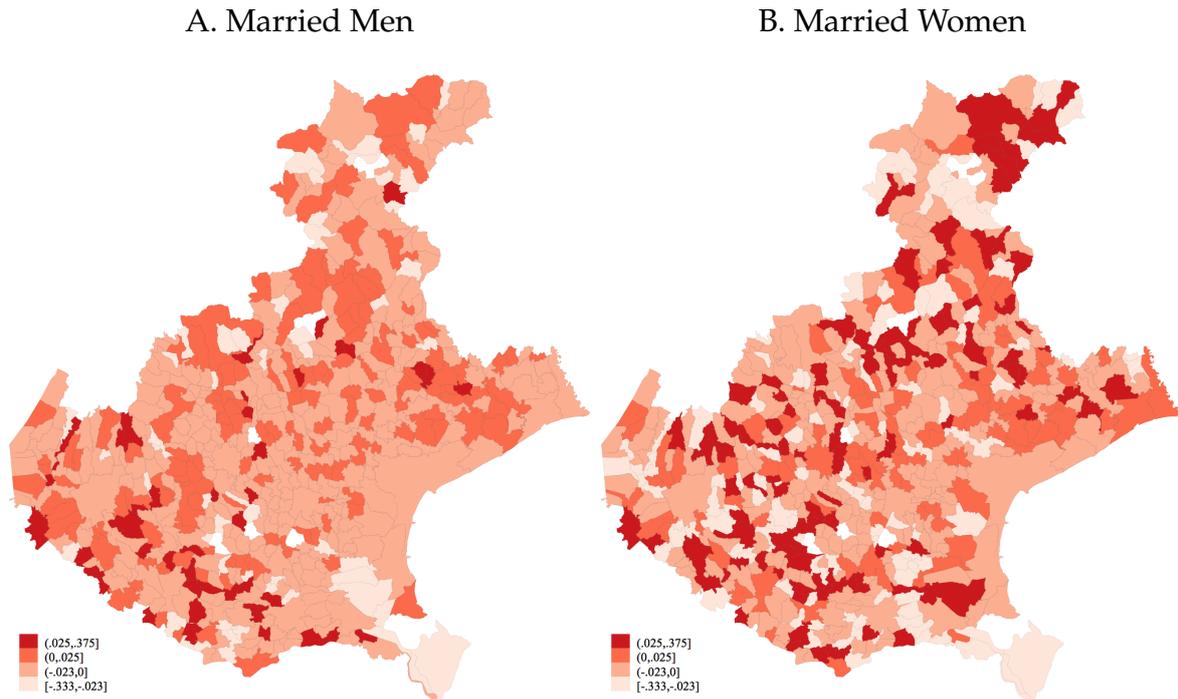
To offer prima facie evidence on the impact of the spouse tax credit on second earners' reported income, [Figure 1](#) depicts the fraction of married men (left-hand side graph) and married women (right-hand side graph) located below the cutoff determining spouse tax credit eligibility (i.e., taxpayers reporting income between 840.51 and 2,840.51 euros) with respect to the fraction of taxpayers reporting income above the cutoff (i.e., between 2,840.52 and 4,840.51 euros). To ensure comparability, the two graphs share a common scale, with darker (lighter) areas denoting municipalities where the portion of taxpayers located below the cutoff is relatively larger (smaller).

Two main remarks emerge from this figure. First, there are gender differences in the probability of reporting income below the spouse tax credit cutoff: women are much more likely to report incomes below the spouse tax credit than men. Second, the figure shows substantial geographical dispersion in the share of taxpayers located below the spouse tax credit cutoff. For instance, gender differences in the fraction of taxpayers located just below the cutoff are negligible in municipalities located around the Adriatic sea (South-East in the map). This area, mostly composed of municipalities located in the Venice province, includes municipalities with higher female labor force participation, where gender attitudes are likely to be more pro-

---

<sup>11</sup>For instance, [Saez \(2010\)](#) finds that bunching responses on kink points of the U.S. Earnings Income Tax Credit (EITC) are exclusively concentrated among EITC recipients with self-employment income. EITC recipients with only wage earnings display no evidence of bunching. [Kleven et al. \(2011\)](#) find that there is virtually no tax-related manipulation in wage earnings of audited Danish taxpayers because of third-party reporting by firms.

Figure 1: Map of Taxpayers' Fraction Located Below the Spouse Tax Credit Cutoff



*Notes:* These figures show the distribution of taxpayers located below the spouse tax credit cutoff across municipalities in the Veneto region. The left hand-side graph focuses on married men; the right hand-side graph on married women. For each municipality, we report the difference between the fraction of taxpayers declaring an income below the spouse tax credit threshold (between 840.5 and 2,840.5 euros) and the fraction of taxpayers declaring an income above it (between 2,841.5 and 4,840.5 euros). To ensure comparability, the two graphs share a common scale, with darker (lighter) areas denoting municipalities where the portion of taxpayers located below the cutoff is relatively larger (smaller).

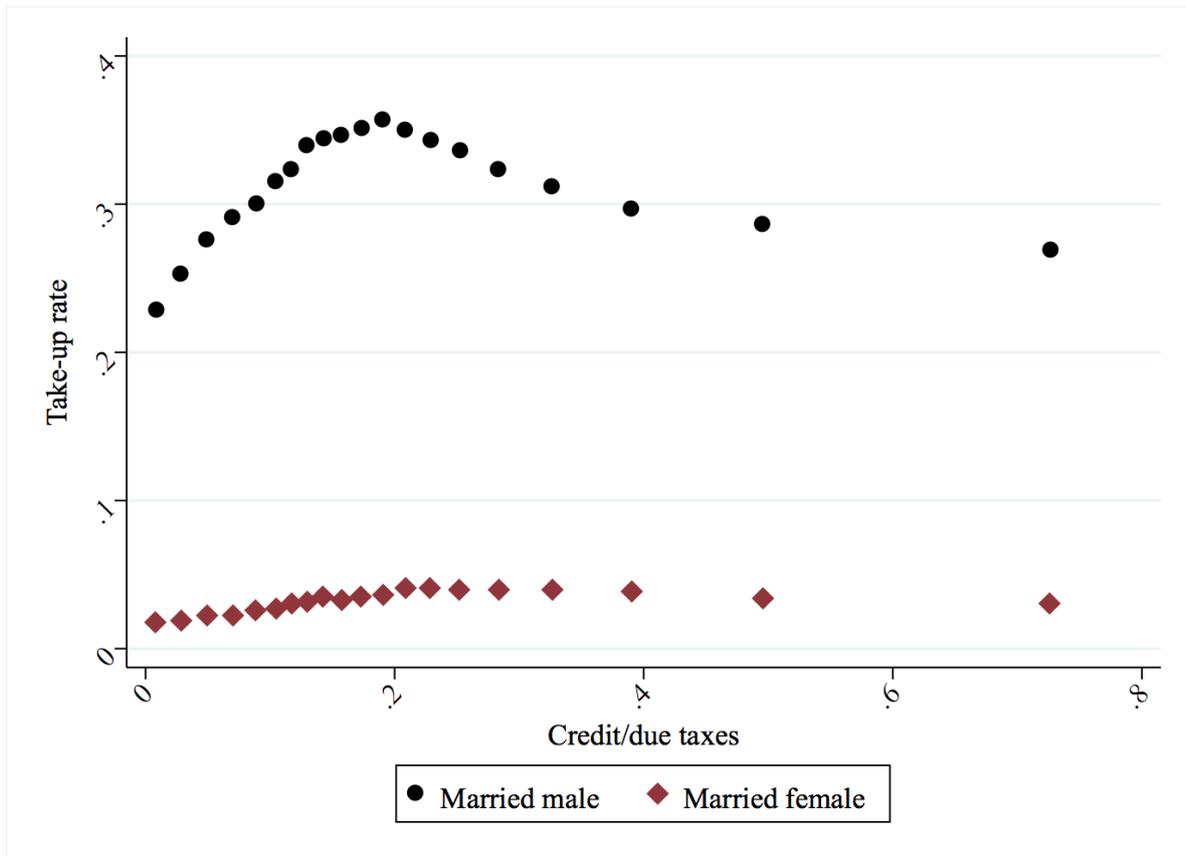
gressive. By contrast, gender differences are more intense in rural areas, such as the mountainous province of Belluno (North-East in the map), where female employment is relatively lower.

Figure 2 depicts the spouse tax credit's take-up rate (as a share of total married taxpayers), separately for married women (red diamonds) and married men (black circles). We present the take up rate in 20 bins of tax credit amount as a share of total tax burden (see appendix Figure A3 for an illustration of the take-up rate by gross income). The pattern emerging from this figure leads to three main observations.

First, there is a gender gap in the spouse tax credit's take up rate. This is not surprising: husbands are more likely to earn more than their wives. Therefore, it is more likely, *ceteris paribus*, that wives' income is reported below the cutoff, making husbands eligible for the tax credit.

Second, men's take-up rate presents an inverted U-shaped pattern over the tax credit distribution. Intuitively, when the tax credit matters less (as a share of the main earner's tax burden), the take-up rate is low because the economic returns are relatively smaller. The take-up rate then linearly increases up to the point where

Figure 2: Take-Up Rate of Spouse Tax Credit



*Notes:* This binscatter shows the take-up rate of spouse tax credit between married men (black circles) and married women (red diamonds) as a function of the tax credit (as a share of the total gross tax burden). Since taxpayers reporting less than 5,000 euros do not pay taxes, the sample includes all married taxpayers with income above 5,000 euros.

the tax credit accounts for around one-fifth of the main earner’s tax bill. However, when the tax credit is high enough, the take-up rate starts to gradually decline. One explanation for this pattern is that the second earner’s market income becomes an importance source of total family income at main earner’s low income levels, when the tax credit matters relatively more. Therefore, second earners’ wives become more likely to contribute to family income by reporting income well above the tax credit cutoff.

Finally, the women’s take-up rate distribution is fairly flat. This result could suggest that second earner husbands’ decision to bunch at the cutoff determining spouse tax credit eligibility does not respond to economic incentives faced by their wife. To investigate this relationship more formally, we study bunching responses at the spouse tax credit cutoff. We present this approach below.

## 3 Conceptual Framework and Empirical Strategy

### 3.1 Conceptual Framework

This section sets out a simple conceptual framework that incorporates gender identity norms in the standard model of household behavior. We study behavioral responses to the spouse tax credit notch building from the seminal contributions of Saez (2010), Chetty et al. (2011), and Kleven and Waseem (2013).

#### 3.1.1 Benchmark Model

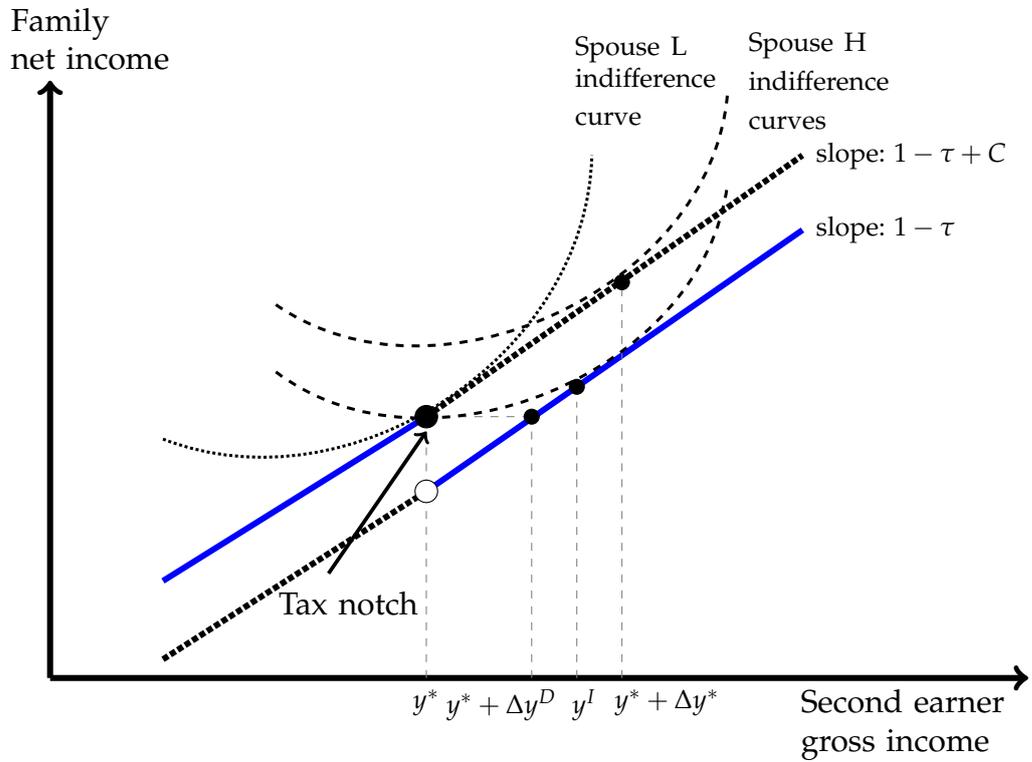
The spouse tax credit creates a “notch” in the budget constraint of families, that is a discontinuity in the choice set of second earner gross income versus family (net) income. Under the conventional (collective) model of household behavior (see, e.g., Chiappori 1988; Chiappori 1992; Apps and Rees 1996; Blundell et al. 2007), this notch should induce second earners, who would otherwise report more income, to instead bunch right at the tax credit cutoff.

Figure 3 offers a simple illustration of how second earners would respond to the spouse tax credit notch. Panel A presents a budget set diagram; panel B the density distributions. Before couple formation, second earners report gross income,  $y$ , that maximizes their own utility subject to their budget constraint. Income is distributed according to a smooth density distribution  $h(y)$  and any heterogeneity is due to preferences or idiosyncratic shocks. When individuals marry and an household is created, the second earner in the couple will face a tax notch at income level  $y^*$ . The notch generates a region of strictly dominated choice in the second earner’s income interval  $(y^*, y^* + \Delta y^D]$ , where she or he can increase both leisure and consumption (family net income) by moving to the notch point  $y^*$ . At this income level, second earners maximize their family net income by letting their spouse to claim a spouse tax credit  $C$ . All second earners located in the income interval  $(y^*, y^* + \Delta y^*]$ , where the bunching region is larger than the area of strictly dominated choice,  $\Delta y^* > \Delta y^D$ , will respond to the spouse tax credit tax notch by bunching.

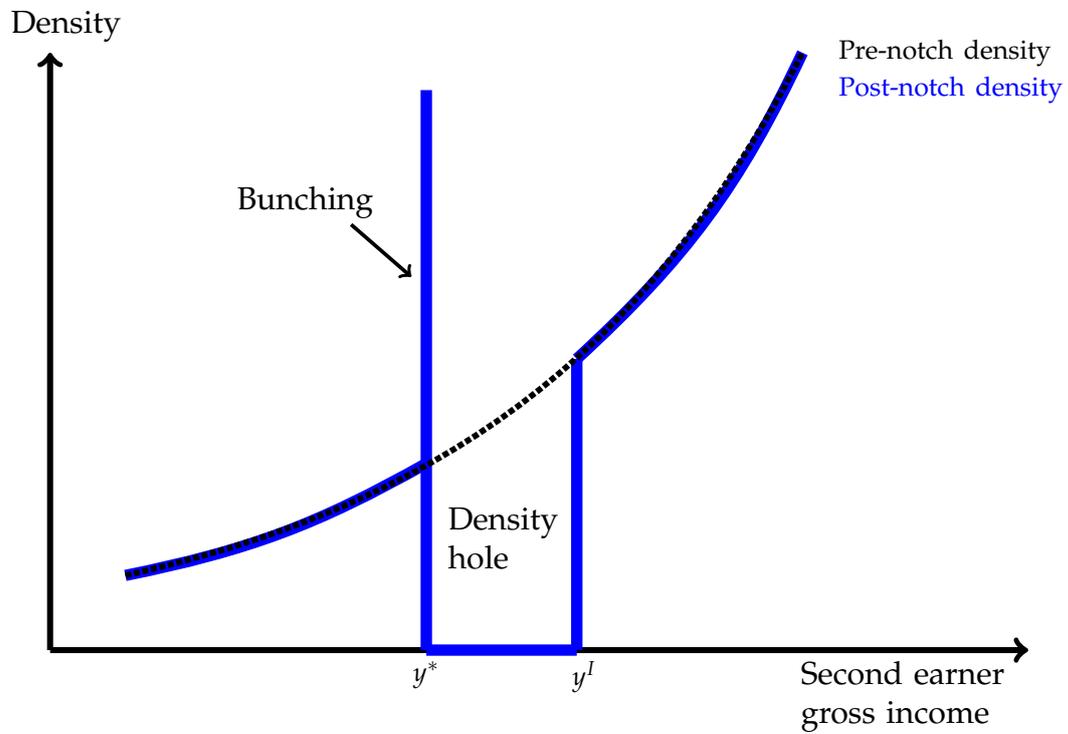
The figure offers an example of behavioral responses from two types of “bunchers”. We define spouse L as the one with the lowest income before couple formation,  $y^*$ ; spouse H as the one with the highest income before couples couple formation,  $y^* + \Delta y^*$ . When a household is created, spouse L will continue to choose income  $y^*$ , making his or her spouse eligible for the tax credit  $C$ . Spouse H will also bunch at the tax notch because is exactly indifferent between the notch point  $y^*$  and the interior point  $y^I$ . Spouse L and H represent the two extreme cases: each spouse between L and H will bunch at the spouse tax credit notch after couple formation. Therefore, because no one is willing to locate between the spouse tax credit notch  $y^*$  and the

Figure 3: Behavioral Responses to a Spouse Tax Credit Notch

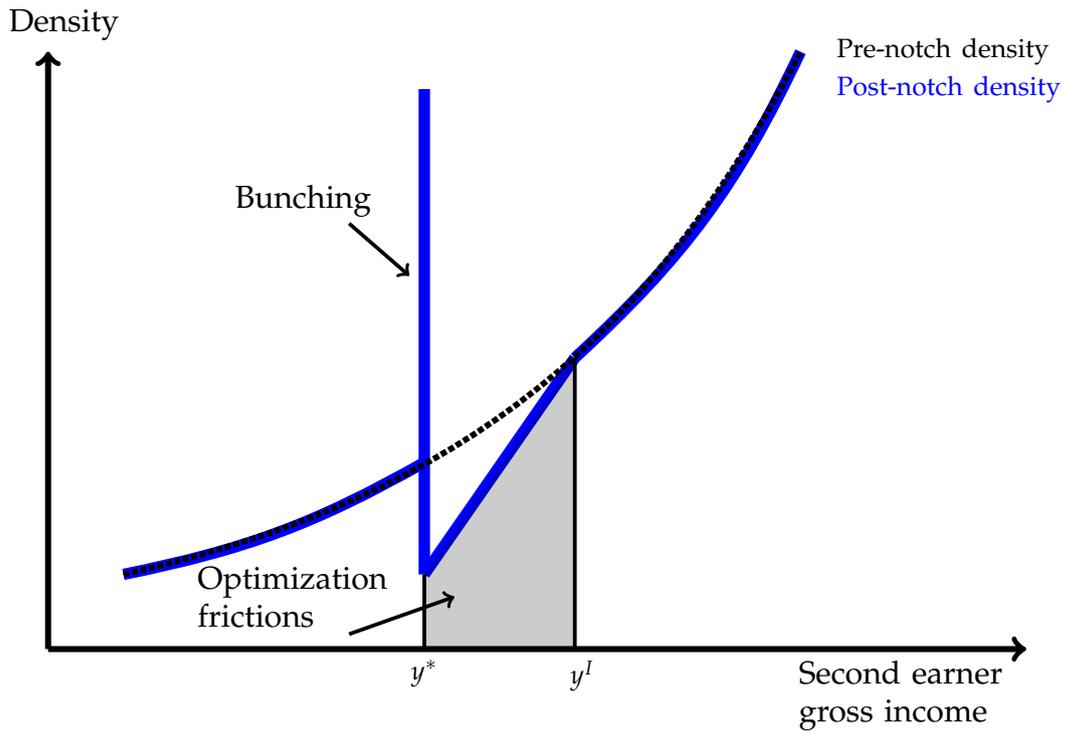
A. Budget Sets



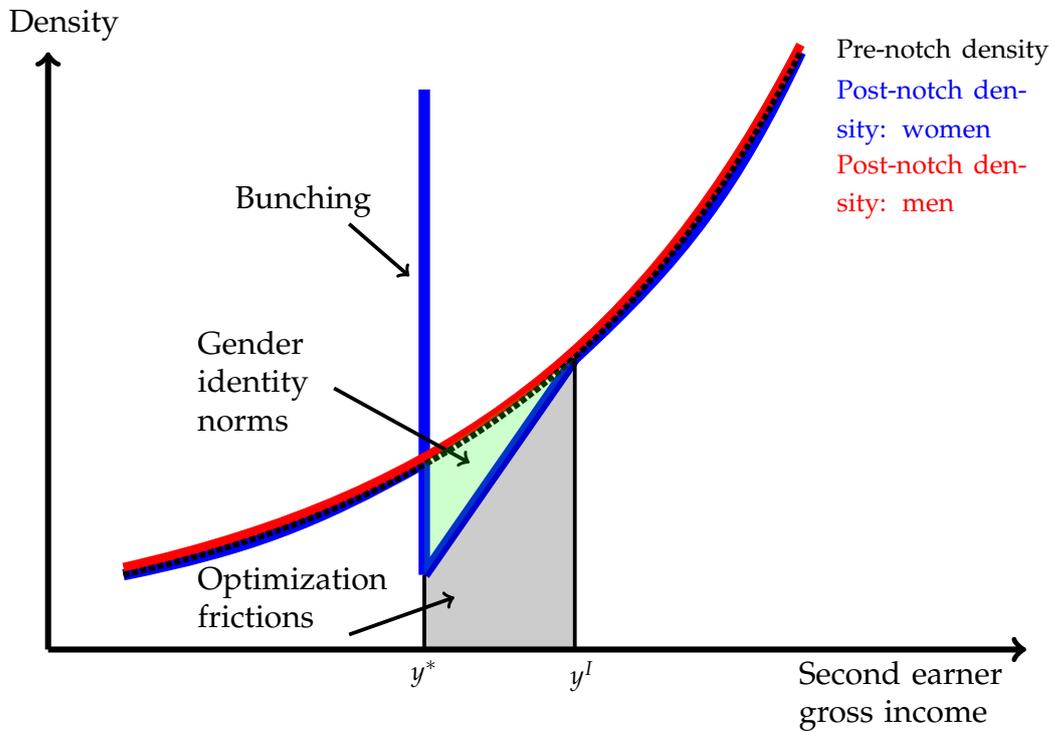
B. Density Distributions



### C. Optimization Frictions



### D. Gender Identity Norms



interior point  $y^l$ , this model would predict a *density hole* in the segment  $(y^*, y^l]$  and *excess bunching* at the spouse tax credit notch  $y^*$ .

Assuming that the counterfactual density  $h_0(y)$  is roughly constant on the bunching segment  $(y^* + \Delta y^*)$ , we can denote excess bunching at the spouse tax credit notch as:

$$B = \int_{y^*}^{y^* + \Delta y^*} h_0(y) dy \approx h_0(y^*) \Delta y^*. \quad (1)$$

### 3.1.2 Gender Identity Norms and Other Optimization Frictions

The predictions of the benchmark model can be questioned by optimization frictions, such as adjustment costs or inattention. Panel C of [Figure 3](#) incorporates optimization frictions (depicted by the gray shaded area) into the model. The key implication is that frictions prevent spouses from bunching, generating a significant density mass in the (otherwise empty) strictly dominated region. In addition to these (standard) optimization frictions presented above, we introduce a new source of frictions: gender identity norms.

Why and how gender identity norms would affect behavioral responses to the spouse tax credit? Bringing insights from social psychology into economics, [Akerlof and Kranton \(2000\)](#) propose a model where one's identity directly enters the utility function. Identity norms can influence economic outcomes because deviating from the behavior that is expected for one's social category is assumed to decrease utility. Hence, people's economic actions can in part be explained by a desire to conform with one's sense of self. Relating the identity model to the concept of gender identity, the two relevant social categories are "man" and "woman", each associated with specific behavioral prescriptions which, if violated, will decrease utility.

A large literature has emphasized that traditional gender roles and women's more prominent role in non-market work may negatively affect women's labor market outcomes (see, e.g., reviews in [Bertrand 2011](#), [Goldin 2014](#), [Blau and Kahn 2017](#), and [Bertrand 2020](#)). For instance, in family specialization models à la [Becker \(1991\)](#), married men mostly focus on working, while their wives are responsible for non-market production. In couples that embrace the male breadwinner model, women would be willing to reduce their labor supply and underinvest in their career, while men would adopt behaviors that allow them to "fill the gap" when the male breadwinner model fails.

The implications of gender identity norms are presented in panel D of [Figure 3](#), where frictions due to gender identity norms are represented by the green triangular area. The presence of gender identity norms implies that second earner men may be unresponsive and stay above the notch, while women would continue to bunch at

the tax notch. This result suggests that the density distribution of second earner *men* would be smooth around the spouse tax credit notch (as depicted by the red solid line in the graph), while the density distribution of second earner *women* would still present very sharp bunching.

### 3.1.3 Dynamics and Career Concerns

As a benchmark, we have considered a static model. However, if career concerns are important, the spouse tax credit affects not only current income, but also income reported in the future. Bunching responses in a multi-period decision context would include intertemporal substitution effects and might dampen the static (annual) bunching response.<sup>12</sup> To evaluate this implication, consider a dynamic framework where current income affects future income (due, e.g., to savings or through effects on earnings from learning by doing, job promotions, etc.). If there is a positive and continuous correlation between current and future income, then the dominated range would be smaller and the “optimal” bunching response lower. At the spouse tax credit notch, *current* net family income is discretely higher than at the point corresponding to the end of the strictly dominated choice region, but *future* net family income is only infinitesimally larger.

These arguments suggest that dynamic behavioral responses to the spouse tax credit notch can have important implications. Under a “static” perspective, bunching responses can be systematically smaller or even absent among second earner women whose utility returns from complying with gender identity norms do not offset the costs of career deterioration and future income losses. In the words of the identity model à la [Akerlof and Kranton \(2000\)](#), a “woman” might behave as a “man” when gender identity norms are less traditional and women do care about their future income prospects.

In a “dynamic” perspective, the cost of gender identity norms for women’s career would be exacerbated if there are hysteresis effects in bunching response. For instance, if gender identity norms activate with marriage and then persist over the entire couple life, gender differences in bunching responses at the spouse tax credit notch would be persistent. This result would be important not only for efficiency considerations, but also for gender inequality.

## 3.2 Identification Strategy

We study whether the second earner’s gender affects family income maximization choices by examining bunching responses at the spouse tax credit notch. Following

---

<sup>12</sup>For instance, [Martínez et al. \(2021\)](#) estimate small intertemporal labor supply substitution responses among wage earners, but stronger responses from self-employees at the intensive margin.

previous studies (Saez 2010; Chetty et al. 2011; Kleven and Waseem 2013), we start by grouping taxpayers in  $j$  bins of gross income and calculate the number of taxpayers in each bin,  $n_j$ . To account for the fact that the density distribution around the tax notch determining tax credit eligibility might differ by gender (due, e.g., to gender income gaps), we estimate gender-specific counterfactual distributions. We define an excluded range around the tax credit cutoff  $[m_L, m_U]$ , such that  $m_L < 0 < m_U$ , and we then run regressions as the following:

$$n_j = \sum_{i=0}^p \beta_i \cdot (m_j)^i + \sum_{i=L}^U \gamma_i \cdot 1(m_j = i) + u_j, \quad (2)$$

where the first term on the right-hand side is a  $p$ -th degree polynomial that accounts for potential curvature in the counterfactual density; the second term is an indicator function for bins located in the excluded range. Following Chetty et al. (2011), our baseline approach uses a seventh-degree polynomial ( $p = 7$ ). To determine the excluded range, we follow the procedure proposed by Kleven and Waseem (2013): the lower bound is determined by visual inspections, determined as the point where excess bunching starts to emerge; the upper bound is computed such that excess bunching below the notch equals the missing mass above the notch.

We can then calculate counterfactual bin counts as the predicted values from equation (2) omitting the contribution of dummies in the excluded range:

$$\hat{n}_j = \sum_{i=0}^p \beta_i \cdot (m_j)^i. \quad (3)$$

We estimate excess bunching by comparing the observed and counterfactual gross income distributions:

$$\hat{B} = \sum_{j=L}^0 (n_j - \hat{n}_j). \quad (4)$$

The excess bunching estimate,  $\hat{B}$ , computes the difference between the observed density of taxpayers located in the excluded range and the counterfactual distribution. For instance, a  $\hat{B} = 1$  would suggest that the excess mass around the tax notch is 100 percent of the average height of the counterfactual distribution within the dominated area range. A larger  $\hat{B}$  estimate would imply a greater distortion in reported income by second earners due to the tax credit.

Following Chetty et al. (2011), we compute the standard error of  $\hat{B}$  by using a parametric bootstrap procedure in which a large amount of gross income distributions are generated by random resampling the error term  $u_j$ . This procedure generates a new set of counts that can be used to calculate new  $\hat{B}$  estimates. We can then

define the standard error of  $\hat{B}$  as the standard deviation of the distribution of  $\hat{B}$  that we obtain through this iterative procedure.<sup>13</sup>

## 4 Gender Differences in Bunching Responses

### 4.1 Bunching Responses to the Spouse Tax Credit

We present our main empirical results in [Figure 4](#), which plots the empirical distribution of gross income by gender. The top panel presents histograms of gross income distribution. To construct these histograms, we first group taxpayers in 150 euro bins of gross income, and then we calculate the fraction of taxpayers in each bin around the tax credit cutoff (demarcated by the dashed vertical line). We plot the taxpayers' distribution up to an income level of 25,000 euros.<sup>14</sup>

The figure shows that there is a spike in the fraction of female taxpayers just below the tax credit cutoff (right panels). By contrast, the distribution of male income is smooth and do not present any visible spike at the tax credit cutoff (left panels). Although the shape of the income distribution differs by gender (due, e.g., to gender income gaps), we do not detect any visible spikes at other points of the gross income distribution.

The bottom graphs offer a comparison of the observed distributions (blue dots) with the counterfactual distribution (red solid line). We also report excess bunching estimates, obtained from equation (4), and bootstrapped standard errors. The figure provides clear evidence of gender differences in bunching response to the spouse tax credit. Relative to the counterfactual distribution, there is a clear excess mass of female earners reporting income just below the cutoff, while we do not observe any excess mass in the distribution of male taxpayers. We estimate excess bunching of 1.238 (-0.008) times the height of the counterfactual distribution of women (men). The standard error associated with our excess bunching estimate is 0.239 for women, 0.363 for men. The null hypothesis that there is no excess mass at the tax notch relative to the counterfactual distribution is rejected for the female distribution (t-statistics of 5.03), while it is not rejected for the male distribution (t-statistics of -0.02).

These estimates suggest that the density of second earner women located in an income range strictly below the tax credit cutoff is 1.238 times larger than the density

---

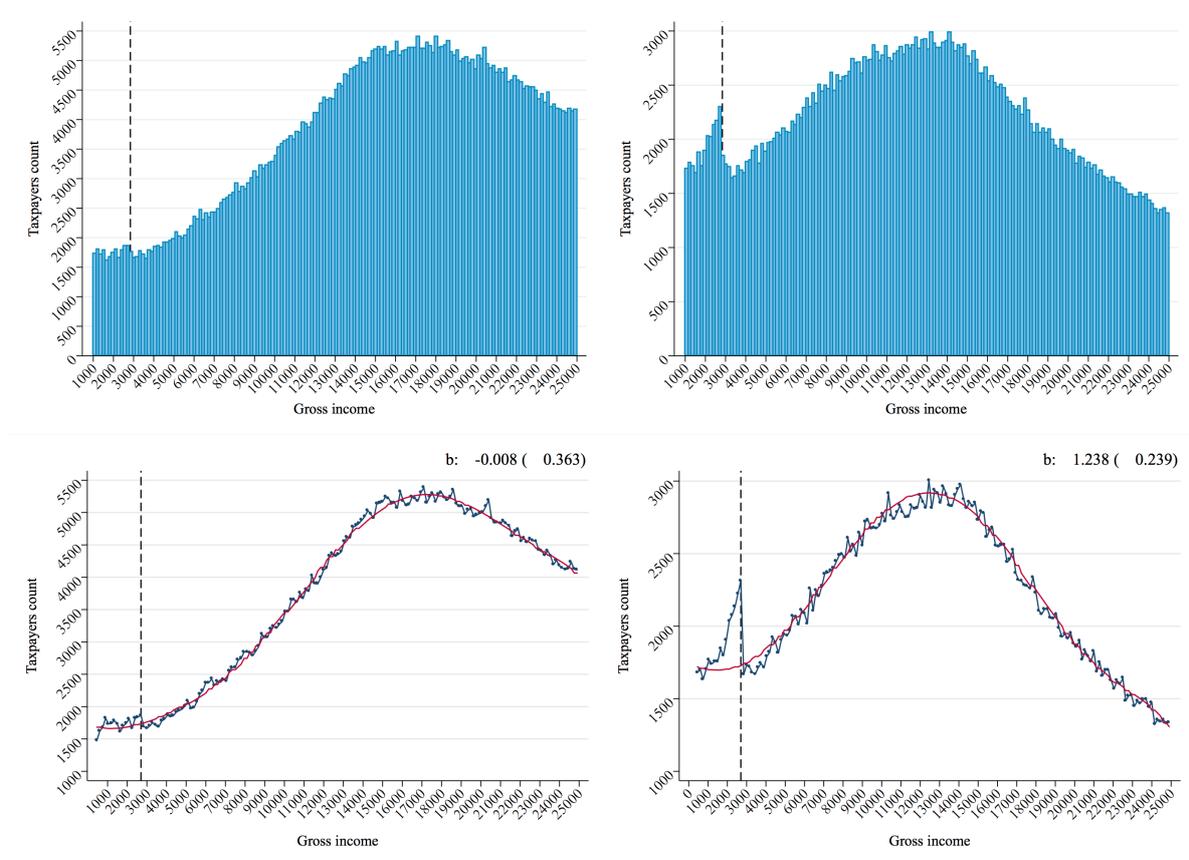
<sup>13</sup>Since we observe the actual income distribution, the estimated standard error mostly reflects misspecification of the polynomial used to estimate the counterfactual distribution, rather than sampling errors.

<sup>14</sup>In these graphs, we do not make any restriction on our sample of self-employees taxpayers. In [Appendix Figure A4](#), we show that our results are remarkably similar when we remove spouse tax credit recipients. Their inclusion does not affect our bunching estimate since they are mostly located at an income level that is well above the tax credit cutoff, thus not affecting the counterfactual distribution.

Figure 4: Bunching Responses to the Spouse Tax Credit

A. Married Men

B. Married Women



*Notes:* These figures present density distributions around the tax notch determining eligibility for the spouse tax credit (denoted by the dashed vertical line). Left-hand side graphs focus on married male taxpayers; right-hand side graphs on married female taxpayers. In each graph, we report the number of taxpayers (by 150 euros bins) for gross income. The bottom graphs also report counterfactual distributions (in red), bunching estimates and bootstrapped standard errors, computed as described in Section 3.2.

that we would have observed in the absence of the policy. On average, our bunching estimate suggests that the female marginal buncher reduces her taxable income by 1.238 bins, which corresponds to around 186 euros. This estimate suggests that the female marginal buncher reduces her reported income by around 186 euros to let her husband to enjoy a tax credit larger than 689 euros, thus increasing family net income by around 503 euros. The absence of any bunching response from second earner men suggests that, *ceteris paribus*, couples where the husband is the second earner hold around 514 euros less than comparable couples where the wife is the second earner. For the representative family in our sample, this income loss corresponds to around 2.7 percent of the annual net family income.

One interpretation of our result is that couples are more likely to cooperate to maximize family income when the male breadwinner model is fulfilled. Our results provide clear evidence that a significant portion of second earner women maximizes

their family income by responding to the incentives created by the spouse tax credit tax notch. By contrast, men do not actively respond to the policy when they are the second earner in the couple. We will now investigate whether gender differences in bunching response occurs with salient events in couples' life, such as marriage and childbirth.

## 4.2 Bunching Responses Around Marriage

If marriage “activates” the gender identity norm, gender differences in bunching at the tax credit cutoff should emerge right after marriage. Married women will start to spend more time in non-market activities, which could reduce the effort that they put into their market jobs, and thus be more likely to report incomes just below the tax credit cutoff.

To test this hypothesis, we implement a difference-in-differences (DiD) design comparing bunching behavior between female and male taxpayers, before and after the marriage year. We define a dichotomous variable,  $Bunch_{i,t}$ , that is equal to 1 in the first year  $t$  when individual  $i$  reports gross income in an income interval, as defined in Section 3.2, just below the spouse tax credit cutoff. This approach has two main advantages compared to our “static” bunching approach. First, we can account for individual-level unobserved heterogeneity and any time-varying shocks. Second, we can investigate the dynamics of “bunching” behavior around the marriage event.

We run specifications like the following:

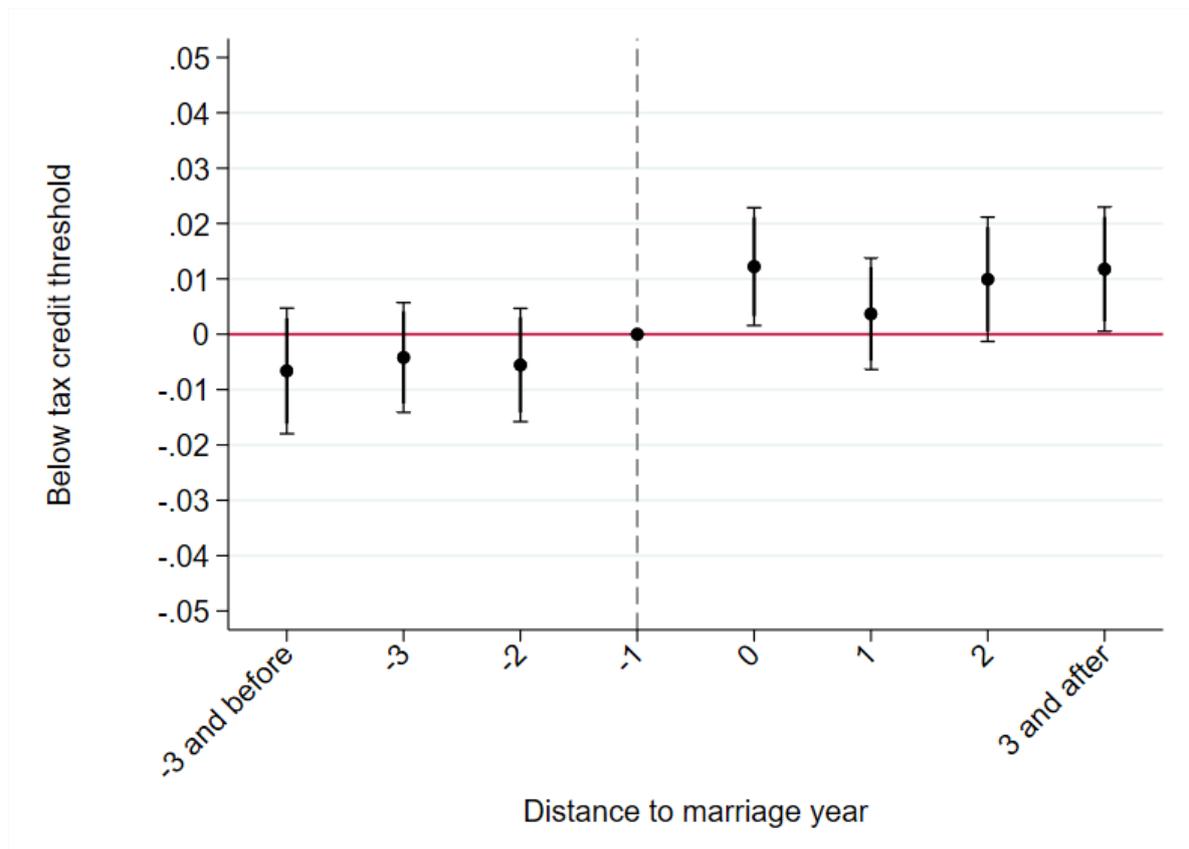
$$Bunch_{i,t} = \sum_{k=-4, k \neq -1}^4 \alpha_k \cdot D_{i,t}^k + \sum_{k=-4, k \neq -1}^4 \beta_k \cdot F_i \cdot D_{i,t}^k + \gamma_i + \delta_{m(i),t} + u_{i,t} \quad (5)$$

where  $Bunch_{i,t}$  is a dummy variable taking value one in the first “bunching” year, that is when a taxpayer reports income just below the spouse tax credit.  $F_i$  indicates female taxpayers and  $D_{i,t}^k$  is a dummy variable for  $k$  years before and after the marriage. The interaction between a dummy for female taxpayers and years,  $F_i \cdot D_{i,t}^k$ , omits the year before marriage (denoted by  $k = -1$ ), so that the DiD coefficient  $\beta_k$  can be interpreted as the probability of reporting income just below the spouse tax credit cutoff in year  $k$  relative to the year before marriage. In the absence of differential pre-existing gender differences in bunching probability,  $\beta_k = 0 \forall k < 0$ . The inclusion of municipality-by-year fixed effects,  $\delta_{m(i),t}$ , allows us to construct potentially more realistic counterfactuals by comparing gender differences in the outcome variable within a given municipality. Individual fixed effects,  $\gamma_i$ , accounts for for any time-invariant individual-specific characteristics or unobserved factors. Finally,  $u_{i,t}$

is an error term. We cluster the standard errors at the individual level.

Figure 5 plots the  $\beta_k$  coefficient estimates and both 90 and 95 percent confidence intervals. The figure provides two main findings. First, there is no significant difference in bunching by gender during the years leading to marriage: the probability that a woman started to report income just below the spouse tax credit cutoff is not significantly different from the men's probability. This result suggests that couples are not formed in a way that would predict eligibility for the spouse tax credit. It is consistent with some studies showing that impact of taxation on marital status is modest (Alm and Whittington 1995; Alm and Whittington 1997; Alm and Whittington 1999).

Figure 5: Bunching Responses Around Marriage Event



Notes: This figure presents gender differences in bunching responses at the spouse tax credit notch around marriage. The figure reports the  $\beta_k$  estimates and both 95 percent (delimited by horizontal bars) and 90 percent (bold line) confidence intervals, obtained from equation (5). The model includes individual fixed effects and municipality-year fixed effects. The coefficient for the corresponding difference-in-differences analysis is 0.013 (standard error = 0.003).

Second, the figure shows that gender differences emerge at marriage. On average, we estimate that, once married, the fraction of women reporting income below the tax credit eligibility cutoff is around 1.3 percentage points larger than the fraction of men. For reference, this effect is equivalent to 19 percent of the baseline gender difference in bunching. This result implies that marriage activates the gender iden-

tity norm, leading wives to be significantly more likely than their husbands to report income below the spouse tax credit cutoff.

### 4.3 Bunching Responses Around Childbirth

This section examines whether childbirth contributes to generate gender differences in bunching behavior. Considerable empirical evidence indicates the existence of a child penalty for women (see, e.g., [Kleven et al. \(2019a\)](#) for cross-country evidence; [Casarico and Lattanzio \(2021\)](#) for the Italian context). While there are a number of reasons that might explain the negative relationship between childbirth and women’s labor market outcomes, some studies have shown that gender norms become more intense around childbirth ([Kuziemko et al. 2018](#); [Boelmann et al. 2021](#)).

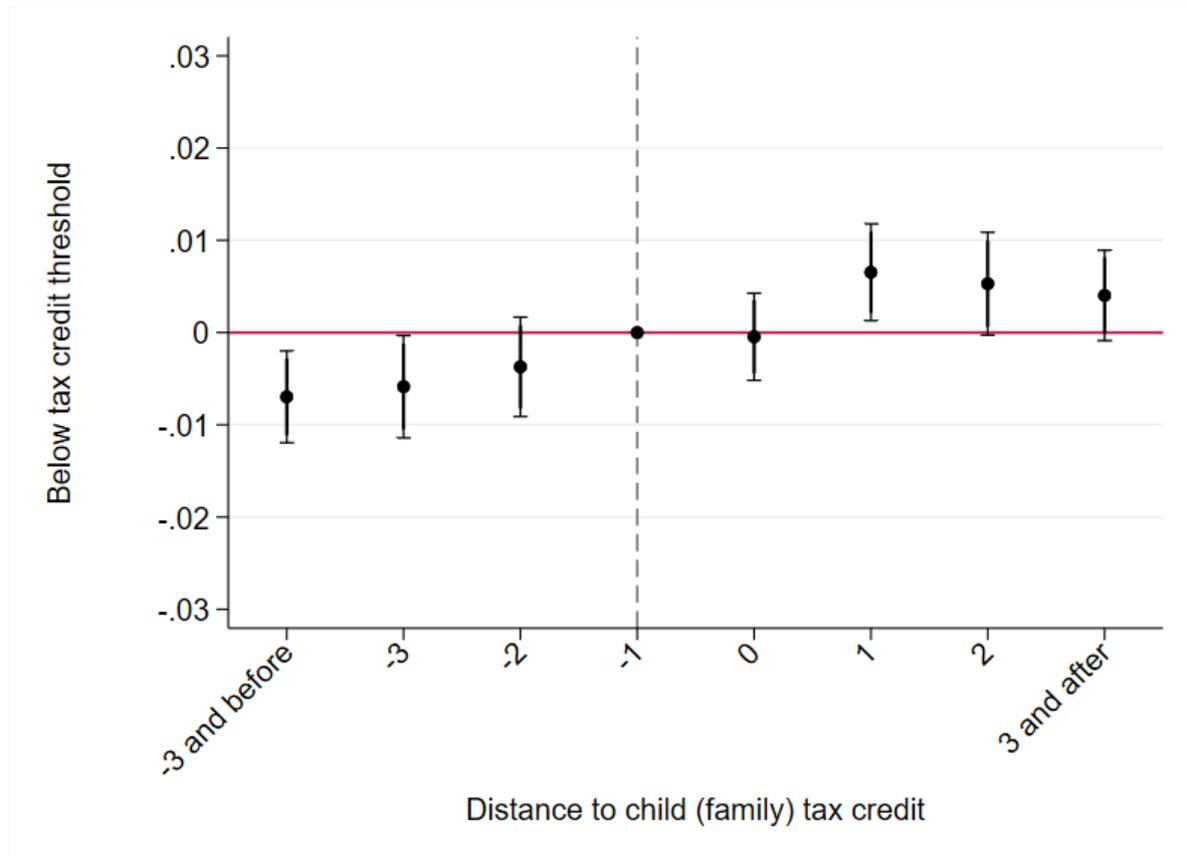
We examine the impact of childbirth by running specifications as in equation (5), but where the event time is defined by the number of years since childbirth. There are two main empirical challenges that we need to tackle. Our first challenge is the definition of the childbirth event, that we do not directly observe in our data. We impute the childbirth year as the first year when a taxpayer receives a child tax credit. Since a child tax credit is received by both parents starting from childbirth, it turns out to be a reasonable proxy for defining the year where the first child was born.

Second, there could be other contemporaneous events taking place at childbirth year. Since, as previously shown, gender differences in bunching began to materialize at marriage, we are concerned that childbirth event times may somehow overlaps with marriage event times, biasing upward our childbirth estimates. Although potentially important, we find that marriage timing perfectly overlaps with childbirth timing just for a negligible portion of our sample (around 1.1 percent of the sample). This suggests that this issue should be not particularly meaningful. Yet, we augment our baseline model with civil status fixed effects to account for the marriage-driven effects that we documented above.

[Figure 6](#) depicts gender differences in bunching behavior around childbirth. The figure reports the  $\beta_k$  coefficient estimates and both 90 and 95 percent confidence intervals obtained from regression as in equation (5), where the event time is the number of years elapsed from childbirth. We find that gender differences in bunching emerged one year after childbirth. On average, we find that women are 0.6 percentage points more likely to bunch than men after childbirth. This effect corresponds to nearly 9 percent of the observed gender difference in bunching before childbirth.

Taken together, these results suggest that gender differences in bunching behavior emerged around two of the two most, if not the most, important events in couples’ life: marriage and childbirth. One explanation for this result is that gender norms

Figure 6: Bunching Responses Around Childbirth Event



Notes: This figure presents gender differences in bunching behavior around the childbirth event, defining as years from receiving a child tax credit. The figure reports the  $\beta_k$  estimates and both 95 percent (delimited by horizontal bars) and 90 percent (bold line) confidence intervals, obtained from equation (5). The model includes individual fixed effects and municipality-year fixed effects. The coefficient for the corresponding difference-in-differences analysis is 0.006 (standard error = 0.002).

turn on around these events.

#### 4.4 Robustness Checks

In principle, our results could be masking gender differences in scope for bunching at the spouse tax credit cutoff. For instance, women might sort into occupations that allow more flexibility in adjusting their reported taxable income (either for labor supply or tax evasion reasons). If there are gender differences in scope for responding to economic incentives, then women would be more responsive to any budget set discontinuity.

To investigate whether this hypothesis may be likely, we study whether gender differences in bunching behavior emerge at other tax notches or kinks where a discontinuity is present in *own* gross versus net income. We focus on two cases: i. a tax notch created by the tax exemption cutoff: self-employed income below 5,000 euros is tax exempted; ii. the marginal tax rate increase - from 15 to 23 percent - at the 15,000

income bracket. If unobservable gender differences in scope for adjusting reported incomes are driving our results, these unobservable characteristics would lead us to observe larger bunching by women at these two points of the income distribution as well. [Figure A5](#) and [Figure A6](#) provide no evidence of gender differences in bunching in both these two cases. This result assuages concerns related to the possibility of gender differences in scope for bunching.<sup>15</sup>

The identification assumption underlying causal inference on gender differences in responses to the spouse tax credit is that the gender-specific income distribution would be smooth in the absence of the tax credit cutoff. We can relax this assumption by examining the distribution of wage earners. Since their earnings are reported by employers, wage earners face substantial frictions in adjusting their reported income. Appendix [Figure A7](#) displays the income distribution for all wage earners, while [Figure A8](#) shows the distributions by gender. We do not detect any significant excess mass in any of these distributions. This yields credence to our identifying assumption.

We then test the sensitivity of our bunching estimates to some assumptions that we make to estimate bunching responses. First, we test whether our estimates are sensitive to different polynomial orders used to estimate the counterfactual distribution. Because we explicitly estimate the upper bound of the dominated range,  $z_u$ , to ensure that excess bunching equals missing mass, one source of bias in  $z_u$  is functional form misspecification. We therefore carry out a sensitivity analysis with respect to the polynomial degree  $p$ . In Appendix [Table A3](#), we show that our baseline bunching estimates are not substantially affected by different order choices of the polynomial.

Second, we test the sensitivity of our estimates to extensive margin responses. Our methodology is robust to extensive margin responses, including real participation responses as well as movements between the formal and informal sectors, as long as they do not take place locally around the tax notch. In this case, the determination of the excluded range should not be substantially affected by extensive margin responses as long as it is defined by a narrow range above the cutoff. In fact, since intensive (bunching) margin responses only occur locally, this approach allows us to identify only intensive margin responses. Yet, since the convergence method described above might rely on a larger range, it is potentially sensitive to extensive margin responses. We test the sensitivity of our estimates to different upper bounds on the income bandwidth where the convergence method is allowed to work. Ap-

---

<sup>15</sup>As long as bunching mostly reflects tax evasion, an alternative explanation is that women are less risk averse than men, and thus more willing to incur in elusive behaviors. Yet, most of the existing evidence points to the opposite direction: in a review of the existing experimental evidence, [Croson and Gneezy \(2009\)](#) report that women are, on average, more risk averse than men.

pendix [Figure A9](#) and [Figure A10](#) show that our male-specific and female-specific, respectively, bunching estimates hold regardless of how we define the income window of interest.

Second earners can respond along two main margins: changes in labor supply or evasion and avoidance responses. Our result holds regardless of what margins underlies changes in second earners' reported gross income. Intuitively, whether the second earner response is through real responses, such as changes in hours worked, or underreporting of true income, will make the main earner eligible for the tax credit anyway. Therefore, distinguishing evasion responses, including within-couple income shifting, from labor supply responses is not critical for the conclusions we draw here, as there are no a-priori reasons to believe that the margin of response could systematically differ depending on the second earner's gender.<sup>16</sup>

These analyses do not completely rule out the possibility that an unobservable difference between women and men is driving our results. For instance, it may be that self-employees low-income men face substantial frictions when adjusting their taxable income, while women do not. Under this explanation, our finding would result from characteristics of second earner women at that specific point of the income distribution. Our next step is to compare second earner men and women at the same income level, but in contexts with different gender identity norms.

## 5 Are Gender Norms Responsible for Bunching?

In this section, we bring additional evidence to bear on the hypothesis that gender identity norms are responsible for our results. We present three exercises. First, we focus on immigrants to test whether gender differences in bunching rate are relatively larger for individuals coming from more traditional societies. Second, we relate cross-cohort gender differences in bunching rate with progressivity of gender views. Finally, we test whether municipality-level gender differences in bunching correlate with different proxies for traditional gender norms.

### 5.1 Immigrants

We start by proposing an epidemiological study of gender norms using foreign-born immigrants. Following [Fernández and Fogli \(2009\)](#), we exploit the “portability” of cultural factors: when individuals emigrate, they may take some aspects of their

---

<sup>16</sup>Since evasion responses and labor supply responses have different normative implications (see, e.g., [Chetty 2009](#)), it would still be useful to distinguish between these two margins of behavioral responses. However, our tax returns data cannot be linked with other dataset, such as matched employer-employee data, providing labor supply information. We are thus unable to distinguish whether reported income responses reflect evasion or labor supply effects in our data.

culture, including gender norms, with them. This suggests that studying immigrants may be a useful strategy for isolating the role of gender norms from other economic and institutional factors. These immigrants, living and working in Italy, face the same markets and institutions, but they potentially differ in their cultural heritage, as reflected in their country of origin. Following [Fernández and Fogli \(2009\)](#), we proxy gender norms with past female labor force participation from the immigrant’s country of origin. We retrieve information on female labor force participation from the World Bank database.<sup>17</sup>

Since immigrants come from different societies, but live and work in the same economic and formal institutional environment, our standard bunching approach would not allow us to investigate how gender norms operate in isolation from other competing factors, such economic factors and institutions of the destination municipality. For instance, it is plausible that immigrants self-select into municipalities that present characteristics (either cultural or institutional) that are closer to those of their origin country. To account for this issue, we estimate bunching responses adjusting for selection in the current municipality of residence. Therefore, our empirical approach compares bunching rates across individuals living in the same municipality, but with different gender norms based on their origin country. Our strategy will thus allow us to study how gender norms operate in isolation from other factors that vary across municipalities. The final sample includes information on 189,007 foreign-born taxpayers (8.9% of which are women), coming from 159 different countries. Since we are interested in second earners that could eventually start to bunch at the spouse tax credit cutoff, we focus only on taxpayers reporting less than 10,000 euros in the first year observed in the data.

Our final model estimates bunching responses, defined as the probability of reporting income just below the spouse tax credit cutoff, with respect to female employment,  $FemEmp_{c(i)}$ , observed in the origin country  $c$  of each immigrant  $i$ :

$$Bunch_{i,t} = \beta \cdot FemEmp_{c(i)} + \gamma_{m(i)} + \delta_t + \eta \cdot X_i + u_i, \quad (6)$$

where  $Bunch_{i,t}$  is equal to 1 if immigrant  $i$  reports income in an income interval just below the spouse tax credit cutoff at year  $t$ . Municipality fixed effects,  $\gamma_{m(i)}$ , account for selection of immigrants across municipalities. To gain precision, we also include year fixed effects,  $\delta_t$ , and a set of individual controls (age and marital status) in  $X_i$ . We cluster the standard errors at the origin country-level. The coefficient of interest,  $\beta$ , computes the effect of a 1 percentage point increase in the origin country’s female employment rate on the probability of bunching. A negative  $\beta$  estimate

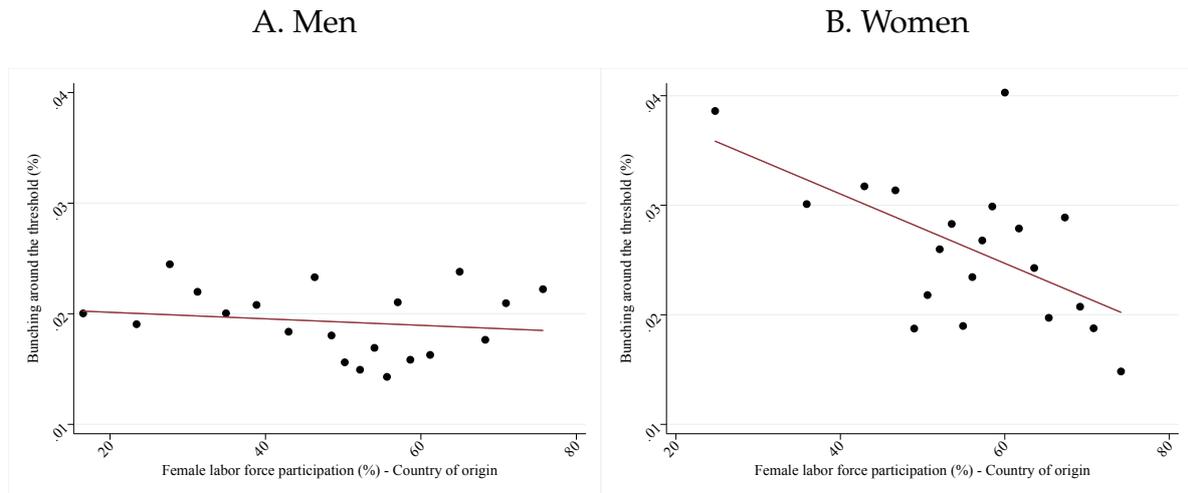
---

<sup>17</sup>Following the classification proposed by the International Labour Organization, female labor force participation is computed relative to the share of female population older than 15. We use the female employment share observed in 2000.

would suggest that bunching behavior is, *ceteris paribus*, more likely among immigrants coming from countries with lower female employment rates. We compute separate  $\beta$  estimates by gender.

Figure 7 presents our results. The figure relates the proportion of male (left-hand side graph) and female taxpayers (right-hand side graph) reporting income below the spouse tax credit cutoff (vertical axis) with origin country's female labor force participation (horizontal axis). The slope depicted in each graph corresponds to the  $\beta$  estimate obtained from equation (6).

Figure 7: Gender Differences in Bunching Among Immigrants



Notes: The figure relates the proportion of male (left-hand side graph) and female taxpayers (right-hand side graph) reporting income below the spouse tax credit cutoff (vertical axis) with the origin country's female labor force participation (horizontal axis). The proportion of taxpayers below the cutoff is defined by the share of (either male or female) taxpayers declaring income between 2,500 and 2,840.5 euros. The scatter-plot controls for municipality fixed effects, year fixed effects, and individual specific controls (age and marital status). The sample includes taxpayers who declared less than 10,000 euros in the first year of the dataset. The  $\beta$  estimate, obtained from equation (6), is -0.003 (standard error=0.005) for male immigrants; -0.032 (standard error=0.009) for female immigrants.

The figure provides striking graphical evidence that gender differences in bunching rates are strongly related to female labor force participation. Conditional on their municipality of residence, women born in high-female employment countries, such as China, are much less likely to report incomes just below the spouse tax credit cutoff, compared to women born in low-female employment countries, such as Iraq or Saudi Arabia. This relationship is statistically significant and economically meaningful: a 10 percentage point increase in origin country's female employment raises the share of women reporting income just below the spouse tax credit cutoff by 0.32 percentage points (the slope coefficient is 0.032, with standard errors of 0.009). By contrast, there is no significant relationship for male taxpayers: the figure presents a flat relationship and the estimated slope is not significantly different from zero.

We believe this result is important for two main reasons. First, this result again

suggests that gender norms are an important determinant of the bunching response to the spouse tax credit. This evidence appears robust to differential selection of immigrants in their municipality of residence. Second, we show that differences in the intensity of traditional gender norms are able to explain not only gender differences in bunching rates, but also across women that grew in contexts that are significantly different in terms of gender norms (as proxied by female employment). The latter result motivates our next empirical exercise: we relate variation in the intensity of bunching responses with variation in proxies for gender norms across individuals and municipalities.

## 5.2 Cross-Cohort Approach

In this section, we compare gender differences in bunching with progressivity of gender views across cohorts. We use data from a nationwide survey conducted by the Italian Institute of Statistics (ISTAT), called *Indagine sulle discriminazioni in base al genere, all'orientamento sessuale, all'appartenenza etnica*, to construct an index of gender roles that varies across cohorts. Specifically, we measure the share of women that strongly agrees with two statements that would likely capture views on traditional gender: i. “men are the main responsible for the provision of family needs”; ii. “men should have more right to a job than women”. The top panel of [Figure 8](#) shows that views about gender norms have become more progressive among younger cohorts. The share of women with very conservative gender norms has decreased by at least 20 percentage points over the last 50 years. Namely, while around one-third of women born in the early post-war period was likely to agree that “men should have more right to a job than women”, just one-tenth of women born in the late 1990s and early 2000s shares this view.

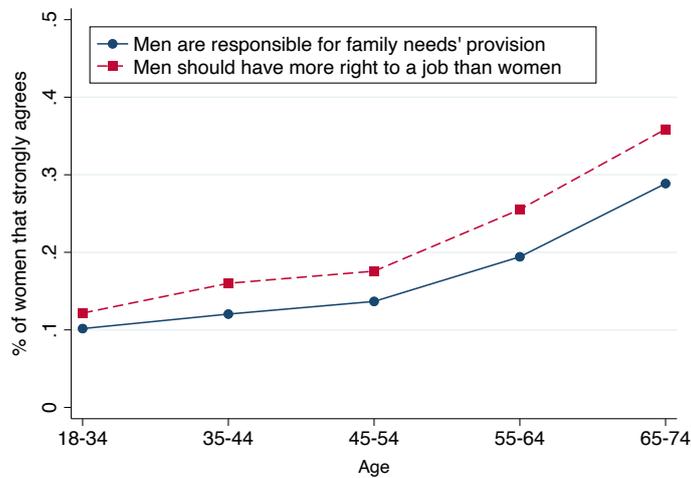
We then investigate whether this pattern mirrors gender differences in bunching rate. The bottom graph presents gender differences by age, where we depict the gender difference in the proportion of taxpayers located barely below the spouse tax credit cutoff. To account for cross-municipality heterogeneity and time-varying shocks, we compute bunching rates controlling for municipality fixed effects, year fixed effects, and civil status. The figure shows that our time series of gender progressivity views mirrors the size of bunching differences by gender, suggesting that gender norms are an important determinant of the size of bunching rate even across cohorts.<sup>18</sup>

---

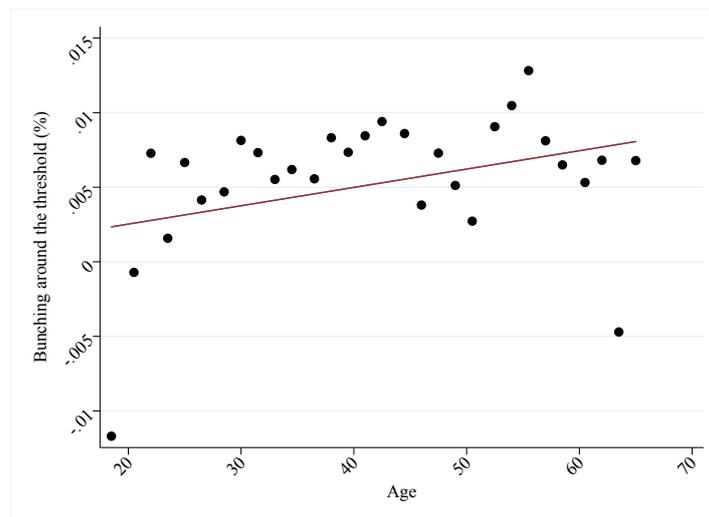
<sup>18</sup>In [Table 2](#), we report unconditional bunching estimates and standard errors estimated for taxpayers above versus below the median age of taxpayers in our sample. Consistent with the evidence presented in the figure, we find that the bunching estimate is statistically significant and large among older women, while it is not statistically significant among younger women and for men (of any age).

Figure 8: Gender Differences in Bunching Are Larger Among the Elderly

### A. Traditional Gender Norms Across Cohorts



### B. Gender Bunching Differences By Cohort



Notes: The left-hand side graph shows the share of female respondents that agree with the following statements: i. “men are the main responsible for the provision of family needs” (blue circles); ii. “men should have more right to a job than women” (red squares). We report estimates by age group (horizontal axis). Data from a nationwide survey conducted by the Italian Institute of Statistics (ISTAT) (see *Indagine sulle discriminazioni in base al genere, all’orientamento sessuale, all’appartenenza etnica*). The right-hand scatter-plot shows the regressions of taxpayers age on taxpayers bunching behaviour (defined as declaring between 2,500 and 2,840.50 euros), in difference between female and male taxpayers. The specification includes municipality fixed effects, year fixed effects, and controls for civil status. The sample includes taxpayers who declared less than 10,000 euros in the first year of the dataset.

## 5.3 Cross-Municipality Approach

This section relates bunching rates with several municipality-level proxies for gender norms. We propose three main proxies, and we then split municipalities according to

whether they score below or above the median value in each of these proxies. First, we construct a municipality-level index of support for the deregulation of abortion in a 1981 referendum.<sup>19</sup> We assume that gender norms are less progressive in municipalities that were less willing to opt for a “yes” in the referendum. Second, we look at the share of female politicians that are elected in the town council over the period covered in our analysis. Our view is that gender norms should be, all else equal, more progressive in municipalities with a higher share of female politicians. Finally, guided by the descriptive evidence from [Figure 1](#), we focus on urban density: we expect that taxpayers living in rural municipalities share more traditional gender norms.

[Table 2](#) shows bunching estimates and standard errors, computed as described in [Section 3.2](#), for married women and married men in each of the sample discussed above. The table provides evidence that bunching estimates among female taxpayers are systematically larger in municipalities with more traditional gender views. In line with our results based on immigrants and across cohorts, we find that differences in the intensity of traditional gender norms seem to have a limited impact on the probability of bunching among men. Taken together, the results emerging from these three analyses suggest that gender differences in bunching are mostly driven by larger responses from women with more traditional gender norms.

---

<sup>19</sup>This referendum, that took place on the 17th of May 1981, asked Italians their opinion on the so-called law 194 (see “*Norme per la tutela sociale della maternità e sull’interruzione volontaria della gravidanza*”), passed three years before.

Table 2: Bunching Responses Are Larger in Municipalities with More Traditional Gender Norms

	Bunching estimate for women		Bunching estimate for men	
	Below median (1)	Above median (2)	Below median (3)	Above median (4)
Support 1981 referendum on free abortion	1.287*** (0.296)	0.101 (0.254)	0.014 (0.401)	-0.314 (0.309)
% of female politicians in town council	1.103*** (0.265)	0.613*** (0.268)	0.149 (0.241)	0.366 (0.255)
Urban density	1.382*** (0.250)	0.316 (0.232)	0.273 (0.273)	-0.032 (0.260)
Age	0.145 (0.261)	1.129*** (0.307)	-0.128 (0.364)	-0.184 (0.366)

*Notes:* This table reports bunching estimates and bootstrapped standard errors, computed as described in Section 3.2, for married female and married male taxpayers. We split our original sample according to whether a municipality ranks below or above the median value of the following variables: i. share of votes that supported the abrogation of free abortion in a 1981 referendum (abrogation of law 194); ii. share of female politicians elected in town council; iii. urban density index. Finally, in the last column, we split taxpayers according to their age.

## 6 Second Earners' Career, Gender Gaps, and Marital Stability

In this section, we first study whether the spouse tax credit generates long-lasting effects on secondary earners' career and on gender income inequalities. Finally, we study whether bunching responses at the spouse tax credit cutoff have implications for marital stability.

### 6.1 Hysteresis in Bunching

Although the economic rationale of the spouse tax credit is to offer insurance against labor market shocks, the policy can *persistently* affect the work and income reporting incentives of second earners. We assess gender differences in bunching hysteresis: how the probability of reporting income below the spouse tax credit cutoff evolves over time by second earners' gender. Focusing on the first individual-specific bunching episode observed in the data, we then estimate the probability that the same individual will bunch in the  $k$ -th year following the first bunching episode.

Formally, we estimate the following model:

$$Bunch_{i,t} = \sum_{j \neq -1} \beta_k \cdot D_{i,t}^k + \gamma_i + \delta_{m(i),t} + \nu_{d(i),t} + \eta \cdot X_{i,t} + u_{i,t}, \quad (7)$$

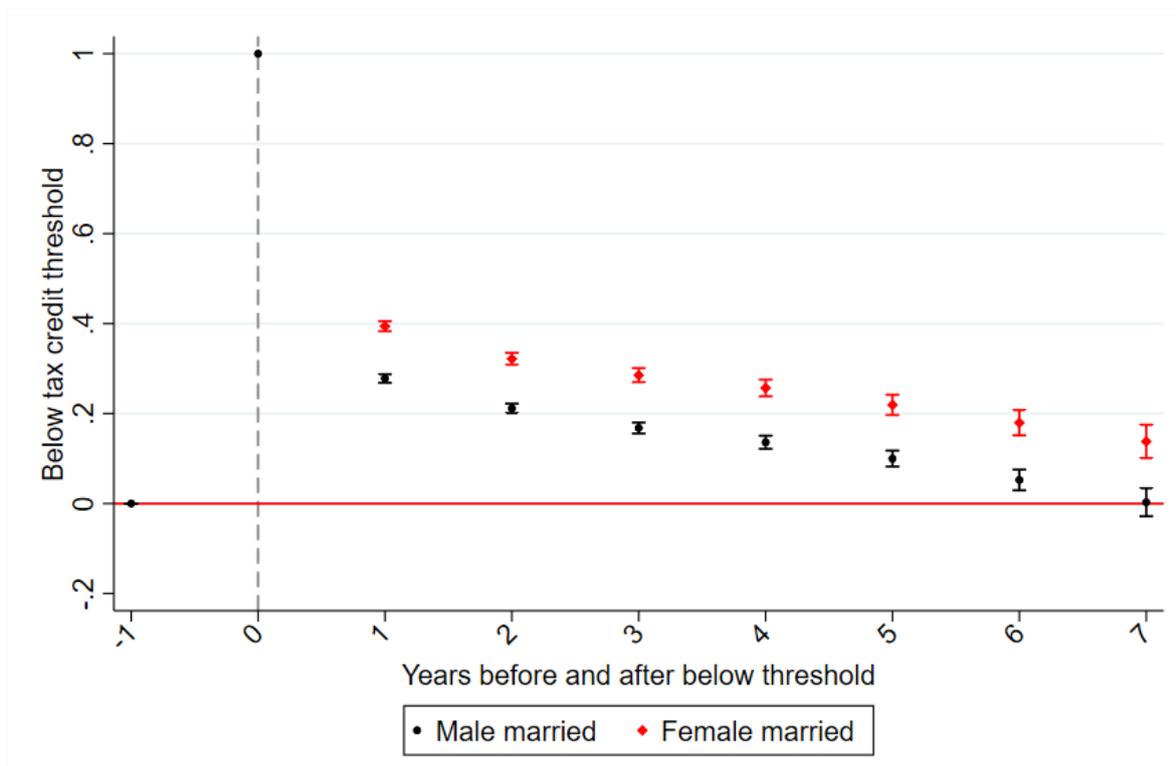
where  $Bunch_{i,t}$  is a dummy variable indicating whether taxpayer  $i$  reports an income level below the spouse tax credit cutoff at year  $t$ . By construction, the outcome variable is equal to 1 for event time  $k = 0$ , that is the first bunching episode observed in the data.  $D_{i,t}^k$  is a dummy variable for  $k$  years after the first bunching episode. The model also includes individual fixed effects,  $\gamma_i$ , year fixed effects interacted with municipality fixed effects,  $\delta_{m(i),t}$ , and decile of initial income (as recorded in the first period) fixed effects interacted with year fixed effects,  $\nu_{d(i),t}$ . These fixed effects allow us to absorb time-varying shocks and to construct more reliable counterfactuals by comparing second earners located in the same local labor markets and starting with a similar level of reported income. Finally  $X_{i,t}$  includes individual time-varying controls. Standard errors are clustered at the individual-level. Our coefficient of interest,  $\beta_k$ , tells us what is the probability that an individual will bunch again after  $k$  years since the first observed bunching episode. We estimate the  $\beta_k$  separately by gender.

Figure 9 presents the  $\beta_k$  coefficient estimates, specifically for married male and married female taxpayers. The figure shows the probability of bunching from year +1 ( $\beta_k = 1$ ) up to year +7 ( $\beta_k = 7$ ) compared to the first bunching year. We also report 90 percent and 95 percent confidence intervals. The figure delivers key two results. First, we show that the spouse tax credit persistently affects the income reporting incentives (either for labor supply or evasion reasons) of secondary earners. By incentivizing second earners to report income below a (small) income threshold, the policy thus limits income growth of secondary earners.

Second, there is a striking evidence of gender differences in bunching persistence. We find that the probability of bunching in the year following the first bunching episode is around 17 percentage points larger for women with respect to men (41 versus 24 percent, respectively). This gender difference survives for many years: after 7 years since the first bunching period, there is still a significant 20 percent probability of a bunching response from women, while the corresponding probability for men is not significantly different from zero. This result has direct implications for gender income inequalities, that we are going to discuss below.<sup>20</sup>

<sup>20</sup>In order to shed light on the mechanism, we conduct this analysis excluding from the sample those taxpayers whose marriage or childbirth year coincides with the first bunching episode. Figure A11 shows this test. The results are very similar, suggesting that the persistency below the threshold mostly results from the first bunching episode and not from other salient events.

Figure 9: Dynamic Responses to the Spouse Tax Credit



Notes: This figure shows the probability of lingering in bunching, separately by gender. The figure reports the  $\beta_k$  coefficient estimate obtained from regressing equation (7), along with 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals. Each coefficient estimate depicted in the graph tells us what is the probability that an individual will bunch again after  $k$  years since the first observed bunching episode (year 0 in the graph). We depict the  $\beta_k$  estimates for men (black circles) and women (red squares). Year -1 and year 0 estimates are mechanical.

## 6.2 The Impact of the Spouse Tax Credit on Gender Inequalities

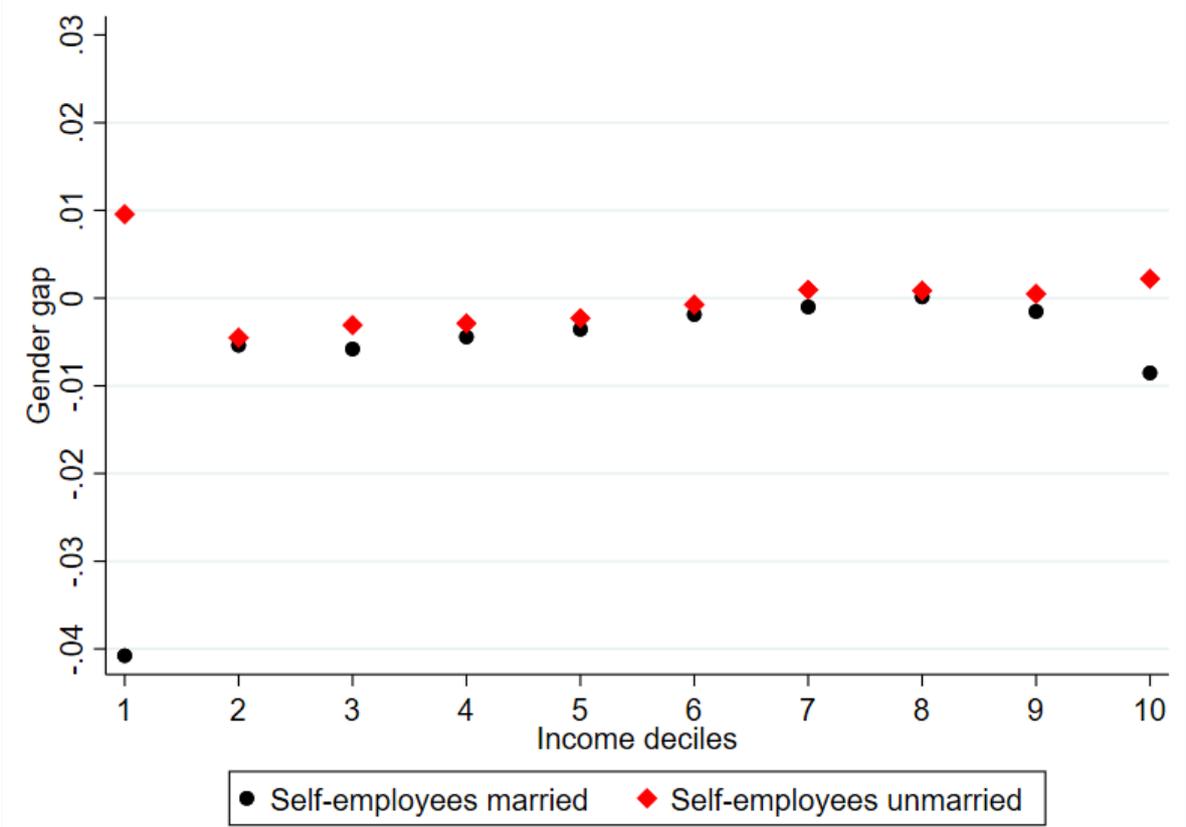
Our analysis has provided two sources of gender differences in behavioral responses to the spouse tax credit. First, married women are much more likely than married men to reduce their income to let their spouse to receive the tax credit. Second, conditional on bunching at the spouse tax credit cutoff, women are more likely to lingering in bunching. Both these effects would positively contribute to generate gender income inequalities. This section aims at provide some prima facie evidence on how much the spouse tax credit, and the the behavioral responses that it triggers, contributes to generate gender income gaps.

To evaluate the impact of the spouse tax credit on the gender income gap, we compute the log difference of male and female declared income in each income decile. We compute this measure for two samples: i. married taxpayers, that are directly affected by the spouse tax credit; ii. unmarried taxpayers, that should be less affected, if any, by the policy.

We present the gender gap in [Figure 10](#). The figure shows that the gross income

of married women are 4 log points lower than those of married men at the first income decile, that is where the spouse tax credit strikes. Significant gender gaps do not emerge at other income deciles, with the notable exception of the top decile. In support of the argument that the tax credit contributes to exacerbate gender income inequalities, we show that the gender gap in the bottom income decile is relatively smaller among unmarried individuals, where the spouse tax credit does not matter by definition.

Figure 10: Gender Gaps Along the Income Distribution



Notes: This figure shows the gender gap by income decile for married (black circles) versus unmarried (red diamonds) self-employees. The gender gap is computed as the logarithm of the income ratio between female and male reported gross income.

Although we cannot rule out alternative explanations for the emergence of a gender gap at this point of the income distribution (e.g., self-selection in married status by low-income women), this result seems to suggest that the spouse tax credit significantly contributes to create gender income inequalities.<sup>21</sup>

<sup>21</sup>According to Casarico and Lattanzio (2019), the raw 2015 average gender earnings gap in Italy is approximately 15 log points. This estimate, however, is not directly comparable with our findings for two main reasons. First, their sample is composed of the universe of private sector employees, while our sample refers to self-employees from Veneto. Second, we focus on the gender income gap rather than the gender earnings gap.

### 6.3 Bunching Responses and Marital Stability

Are couples that coordinate their income reporting behaviors more likely to last longer? Previous research has shown that gender identity norms significantly affect marital stability (Bertrand et al. 2015; Folke and Rickne 2020). Building from this literature, we evaluate whether bunching responses predict marital stability. Namely, we test whether second earner “bunchers” have lower divorce rate than second earner that did not bunch at the spouse tax credit cutoff.

We present this result in Figure 11, which shows the probability of divorce by second earner’s income. The main finding of this figure is that the divorce rate is systematically lower among couples where the second earner bunches at the spouse tax credit cutoff. Second earner women reporting income just below the spouse tax credit cutoff are 1.3 percentage points (20 percent) less likely to divorce, compared to second earner women that report income above the cutoff (top graph). We find similar results for men (bottom graph). This suggestive evidence highlights the fact that adopting behaviors that maximize the family income increases marital stability. Therefore, gender identity norms preventing men to optimize their family income are associated not only with monetary costs, but also with lower marriage durability.

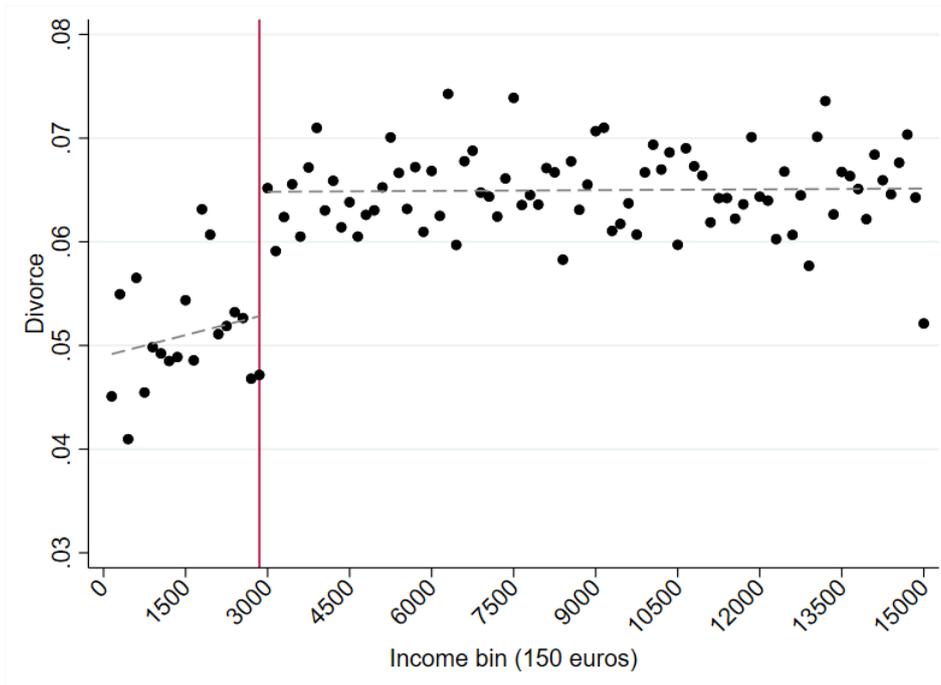
We further investigate the non-monetary costs associated with the violation of gender identity norms in Appendix B. Using data on married couples from 2013 to 2020 survey on Aspects of Daily Life (*Indagine Multiscopo sulle Famiglie: Aspetti della Vita Quotidiana*), we collect information on who is the head of the household. The survey asks questions on a range of topics, including economic outcomes, health status and life satisfaction, allowing us to explore the effect of gender norms violation on several socio-economic outcomes.

We show that the violation of the male breadwinner model has important negative implications on couples’ life and economic satisfaction. Specifically, we present three main suggestive results. First, in couples where the wife’s income exceeds the husband’s, both the wife and the husband report to be less satisfied with their marriage. Relative to comparable couples where the husband is the main earner, couples where the wife outearns the husband are between 1 and 1.6 percentage points less likely to respond to feel “happy” or “very happy” with their marriage. This evidence is similar to previous (more robust) results based on American families (Bertrand et al. 2015). We also show that this effect spreads through the family: when the male breadwinner model fails, daughters are 2.1 percentage points less likely to feel “satisfied” or “very satisfied” about their family, while the impact on sons appears less clear.

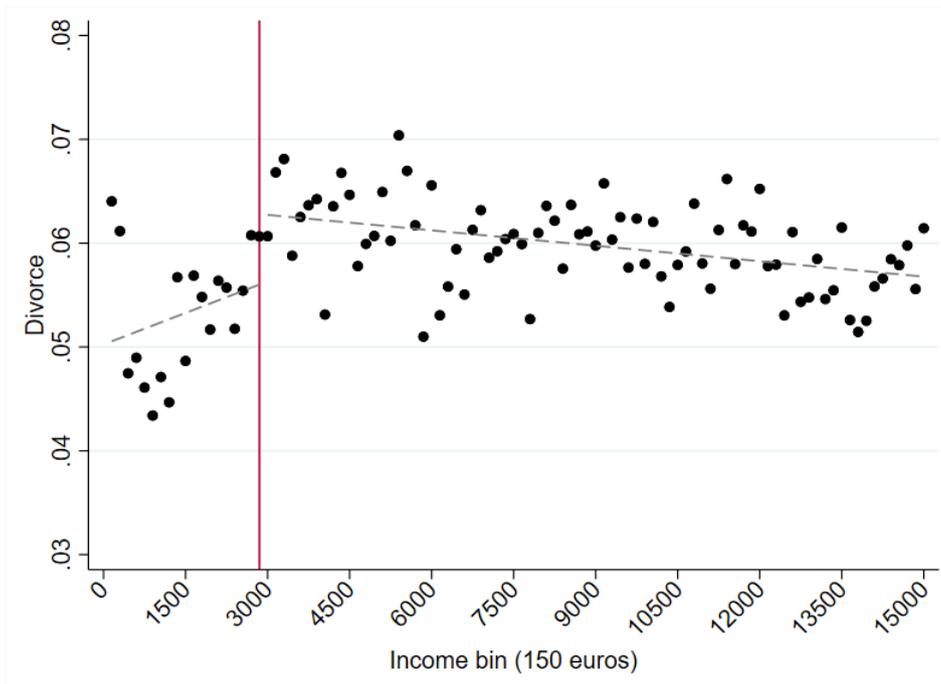
Second, husbands are more likely to report anxiety disorders when the male breadwinner model fails. In couples where the wife is the main earner, husbands are 1.7

Figure 11: Bunching Responses and Marital Stability

A. Women



B. Men



Notes: The plot shows the fraction of divorced or legally separated taxpayers by gender over the income distribution (150 euros income bins). The analysis focuses on incomes below the 15,000 euros threshold.

percentage points more likely to report feelings of anxiety. This result is consistent with social psychology research stating that infringing of internalized rules gener-

ates apprehension and nervousness.<sup>22</sup>

Finally, despite our empirical exercise is based on comparing couples with similar observable economic conditions, we find that wives report to be significantly less satisfied with the economic conditions of their family when they are the main earner in the couple. Taken together, this survey evidence helps to rationalize the association between bunching responses and marital stability: second earners that maximize their family income by bunching at the spouse tax credit cutoff are more likely to remain married.

## 7 Conclusions

This paper studies whether gender identity norms prevent family income maximization. We leverage variation from an Italian policy that grants a large tax credit to the main earner in a couple when the second earner reports income below a cutoff. The policy creates an incentive for secondary earners to bunch at the spouse tax credit cutoff. Using novel tax returns data, we show large bunching responses from second earner women, but no response from second earner men. This result suggests that household decisions are not Pareto-efficient when men are the second earner within the couple. Our bunching estimates allow us to elicit the monetary costs associated with gender identity norms: due to imperfect spouse tax credit take-up, couples where the husband is the second earner hold around 503 euros less than comparable couples where the wife is the second earner.

We show that gender differences in bunching responses emerge after two salient events in couples' life: marriage and childbirth. Consistent with the notion that gender identity norms drive our results, we show that gender differences in bunching responses are relatively larger among immigrants coming from more conservative societies, and natives living in more gender-traditional municipalities.

Finally, we present evidence on the long-term effect of the policy on second earners' career. Although the economic rationale of the spouse tax credit is to offer insurance against labor market shocks, we show that spouse tax credit persistently limits women's income growth. These behavioral responses to the spouse tax credit contribute to create a significant gender income gap. These results suggest that gender identity norms should be taken into account in the design of a more efficient and equitable tax systems.

---

<sup>22</sup>In personality development, researchers agree on the importance of internalization of rules for behavior. For instance, [Thomas \(1996\)](#) points out that identity, or self, must be constantly "defended against anxiety in order to limit disruption and maintain a sense of unity" (p. 284).

## References

- Akerlof, G. A. and Kranton, R. (2000). Economics and Identity. *Quarterly Journal of Economics*, 115(3):715–753. [1](#), [4](#), [15](#), [16](#)
- Akerlof, G. A. and Kranton, R. (2010). *Identity Economics: How Our Identities Shape Our Work, Wages, and Well-Being*. Princeton University Press, Princeton and Oxford. [1](#), [4](#)
- Alesina, A., Giuliano, P., and Nunn, N. (2013). On the Origins of Gender Roles: Women and the Plough. *The Quarterly Journal of Economics*, 128(2):469–530. [4](#)
- Alesina, A. and Ichino, A. (2009). *L'Italia Fatta in Casa. Indagine sulla Vera Ricchezza degli Italiani*. Mondadori. [6](#)
- Alesina, A., Ichino, A., and Karabarbounis, L. (2011). Gender-Based Taxation and the Division of Family Chores. *American Economic Journal: Economic Policy*, 3(2):1–40. [5](#)
- Alm, J. and Whittington, L. A. (1995). Does the Income Tax Affect Marital Decisions? *National Tax Journal*, 48(4):565–572. [21](#)
- Alm, J. and Whittington, L. A. (1997). Income Taxes and the Timing of Marital Decisions. *Journal of Public Economics*, 64(2):219–240. [21](#)
- Alm, J. and Whittington, L. A. (1999). For Love or Money? The Impact of Income Taxes on Marriage. *Economica*, 66(263):297–316. [21](#)
- Apps, P. F. and Rees, R. (1996). Labour Supply, Household Production and Intra-Family Welfare Distribution. *Journal of Public Economics*, 60(2):199–219. [1](#), [12](#)
- Bastani, S. and Waldenström, D. (2021). The Ability Gradient in Tax Responsiveness. *Journal of Public Economics Plus*, 2:100007. [5](#)
- Becker, G. S. (1991). *A Treatise on the Family*. Harvard University Press, Cambridge, MA and London, England. [2](#), [15](#)
- Benny, L., Bhalotra, S., and Fernandez, M. (2021). Occupational Flexibility and the Graduate Gender Wage Gap in the UK. *ISER WP No. 5*. [3](#)
- Bertrand, M. (2011). New Perspectives on Gender. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, chapter 17, pages 1543–1590. North Holland: Elsevier Science, vol.4b edition. [15](#)
- Bertrand, M. (2020). Gender in the Twenty-First Century. *AEA Papers and Proceedings*, 110:1–24. [15](#)
- Bertrand, M., Kamenica, E., and Pan, J. (2015). Gender Identity and Relative Income Within Households. *Quarterly Journal of Economics*, 130(2):571–614. [1](#), [4](#), [35](#)
- Bhargava, S. and Manoli, D. (2015). Psychological Frictions and the Incomplete Take-up of Social benefits: Evidence from an IRS Field Experiment. *American Economic Review*, 105(11):3489–3529. [5](#)

- Blau, F. D. and Kahn, L. M. (2017). The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature*, 55(3):789–865. [6](#), [15](#)
- Blundell, R., Chiappori, P. A., Magnac, T., and Meghir, C. (2007). Collective Labour Supply: Heterogeneity and Non-Participation. *Review of Economic Studies*, 74(2):417–445. [1](#), [12](#)
- Boelmann, B., Raute, A., and Schonberg, U. (2021). Wind of Change? Cultural Determinants of Maternal Labor Supply. *SSRN Electronic Journal*. [22](#)
- Borella, M., Nardi, M. D., and Yang, F. (2022). Are Marriage-Related Taxes and Social Security Benefits Holding Back Female Labor Supply? *Review of Economic Studies*, (forthcoming). [5](#)
- Casarico, A. and Lattanzio, S. (2019). What Firms Do: Gender Inequality in Linked Employer-Employee Data. *WorkINPS paper n. 24*. [6](#), [34](#)
- Casarico, A. and Lattanzio, S. (2021). Behind the Child Penalty: Understanding What Contributes to the Labour Market Costs of Motherhood. *CESifo Working Paper No. 9155*. [3](#), [22](#)
- Chetty, R. (2009). Is the Taxable Income Elasticity Sufficient to Calculate Deadweight Loss? The Implications of Evasion and Avoidance. *American Economic Journal: Economic Policy*, 1(2):31–52. [25](#)
- Chetty, R. (2012). Bounds on Elasticities With Optimization Frictions: A Synthesis of Micro and Macro Evidence on Labor Supply. *Econometrica*, 80(3):969–1018. [5](#)
- Chetty, R., Friedman, J. N., Olsen, T., and Pistaferri, L. (2011). Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence From Danish Tax Records. *Quarterly Journal of Economics*, 126(2):749–804. [1](#), [5](#), [12](#), [17](#)
- Chetty, R., Friedman, J. N., and Saez, E. (2013a). Using Differences in Knowledge Across Neighborhoods to Uncover the Impacts of the EITC on Earnings. *American Economic Review*, 103(7):2683–2721. [5](#)
- Chetty, R., Guren, A., Manoli, D., and Weber, A. (2013b). Does Indivisible Labor Explain the Difference between Micro and Macro Elasticities? A Meta-Analysis of Extensive Margin Elasticities. *NBER Macroeconomics Annual*, 27(1):1–56. [5](#)
- Chetty, R., Looney, A., and Kroft, K. (2009). Salience and Taxation: Theory and Evidence. *American Economic Review*, 99(4):1145–1177. [5](#)
- Chiappori, P.-A. (1988). Rational Household Labor Supply. *Econometrica*, 56(1):63–89. [1](#), [12](#)
- Chiappori, P.-A. (1992). Collective Labor Supply and Welfare. *Journal of Political Economy*, 100(3):437–467. [1](#), [12](#)
- Croson, R. and Gneezy, U. (2009). Gender Differences in Preferences. *Journal of Economic Literature*, 47(2):448–474. [24](#)

- Fernández, R. (2007). Women, Work, and Culture. *Journal of the European Economic Association*, 5(2-3):305–332. [4](#)
- Fernández, R. (2011). Does Culture Matter? In Benhabib, J., Bisin, A., and Jackson, M. O., editors, *Handbook of Social Economics*, volume 1, chapter 11. Elvesier, Amsterdam. [3](#)
- Fernández, R. and Fogli, A. (2009). Culture: An Empirical Investigation of Beliefs, Work, and Fertility. *American Economic Journal: Macroeconomics*, 1(1):146–177. [4](#), [25](#), [26](#)
- Fernández, R., Fogli, A., and Olivetti, C. (2004). Mothers and Sons: Preference Formation and Female Labor Force Dynamics. *Quarterly Journal of Economics*, 119(4):1249–1299. [4](#)
- Folke, O. and Rickne, J. (2020). All the Single Ladies: Job Promotions and the Durability of Marriage. *American Economic Journal: Applied Economics*, 12(1):260–287. [4](#), [35](#)
- Gelber, A. M., Jones, D., and Sacks, D. W. (2020). Estimating Adjustment Frictions Using Nonlinear Budget Sets: Method and Evidence from the Earnings Test. *American Economic Journal: Applied Economics*, 12(1):1–31. [5](#)
- Giuliano, P. (2022). Gender and Culture. *Oxford Review of Economic Policy*, (forthcoming). [4](#)
- Goldin, C. (2014). A Grand Gender Convergence: Its Last Chapter. *American Economic Review*, 104(4):1091–1191. [3](#), [15](#)
- Goldin, C. and Katz, L. F. (2011). The Cost of Workplace Flexibility for High-Powered Professionals. *Annals of the American Academy of Political and Social Science*, 638(1):45–67. [3](#)
- Guiso, L., Sapienza, P., and Zingales, L. (2006). Does Culture Affect Economic Outcomes? *Journal of Economic Perspectives*, 20(2):23–48. [4](#)
- Guner, N., Kaygusuz, R., and Ventura, G. (2012). Taxation and Household Labour Supply. *Review of Economic Studies*, 79(3):1113–1149. [5](#)
- Halla, M., Schmieder, J., and Weber, A. (2020). Job Displacement, Family Dynamics, and Spousal Labor Supply. *American Economic Journal: Applied Economics*, 12(4):253–287. [4](#)
- Ichino, A., Olsson, M., Petrongolo, B., and Skogman Thoursie, P. (2021). Economic Incentives, Home Production and Gender Identity Norms. *SSRN Electronic Journal*. [4](#)
- Ke, D. (2021). Who Wears the Pants? Gender Identity Norms and Intrahousehold Financial Decision-Making. *Journal of Finance*, 76(3):1389–1425. [4](#)
- Kleven, H., Landais, C., Posch, J., Steinhauer, A., and Zweimüller, J. (2019a). Child Penalties across Countries: Evidence and Explanations. *AEA Papers and Proceedings*, 109:122–126. [3](#), [22](#)

- Kleven, H., Landais, C., and Søgaard, J. E. (2019b). Children and Gender Inequality: Evidence from Denmark. *American Economic Journal: Applied Economics*, 11(4):181–209. [3](#)
- Kleven, H. J. (2016). Bunching. *Annual Review of Economics*, 8:435–464. [2](#)
- Kleven, H. J., Knudsen, M., Kreiner, C., Pedersen, S., and Saez, E. (2011). Unwilling or Unable to Cheat? Evidence from a Randomized Tax Audit Experiment in Denmark. *Econometrica*, 79:651–692. [9](#)
- Kleven, H. J. and Waseem, M. (2013). Using Notches to Uncover Optimization Frictions and Structural Elasticities: Theory and Evidence from Pakistan. *Quarterly Journal of Economics*, 128(2):669–723. [1](#), [5](#), [12](#), [17](#)
- Kuziemko, I., Pan, J., Shen, J., and Washington, E. (2018). The Mommy Effect: Do Women Anticipate the Employment Effects of Motherhood? *NBER Working Paper No. 24740*. [22](#)
- Martínez, I. Z., Saez, E., and Siegenthaler, M. (2021). Intertemporal Labor Supply Substitution? Evidence from the Swiss Income Tax Holidays. *American Economic Review*, 111(2):506–546. [16](#)
- Olivetti, C. and Petrongolo, B. (2016). The Evolution of Gender Gaps in Industrialized Countries. *Annual Review of Economics*, 8(1):405–434. [3](#)
- Roth, A. and Slotwinski, M. (2021). Gender Norms and Income Misreporting within Households. *SSRN Electronic Journal*. [4](#)
- Rubolino, E. (2022). Taxing the Gender Gap: Labor Market Effects of a Payroll Tax Cut for Women in Italy. *CESifo Working Paper No. 9671*. [5](#)
- Saez, E. (2010). Do Taxpayers Bunch at Kink Points? *American Economic Journal: Economic Policy*, 2(3):180–212. [1](#), [9](#), [12](#), [17](#)
- Saez, E., Slemrod, J., and Giertz, S. H. (2012). The Elasticity of Taxable Income with Respect to Marginal Tax Rates: A Critical Review. *Journal of Economic Literature*, 50(1):3–50. [2](#)
- Taubinsky, D. and Rees-Jones, A. (2018). Attention Variation and Welfare: Theory and Evidence from a Tax Salience Experiment. *Review of Economic Studies*, 85(4):2462–2496. [5](#)
- Thomas, K. (1996). The Defensive Self: a Psychodynamic Perspective. In Stevens, R., editor, *Understanding the Self*. SAGE Publications, Thousand Oaks, CA. [37](#)
- Winkler, A. E., McBride, T. D., and Andrews, C. (2005). Wives Who Outearn Their Husbands: A Transitory or Persistent Phenomenon for Couples. *Demography*, 42(3):523–535. [6](#)

# Appendices

## A Additional Tables and Figures

Table A1: Personal income tax schedule

Taxable income (euros per-year)	Marginal tax rate (%)
If composed only of income from real estates (up to 500 euros)	0
If composed only of retirement income (up to 7,500 euros) + income from land (up to 185,92 euros) + income from a main residence	0
< 15,000	23
15,001-28,000	27
28,001-55,000	38
55,001-75,000	41
> 75,000	43

*Note:* This table displays information the Italian personal income tax (IRPEF). Taxpayers are exempted from paying income taxes if their income is composed exclusively of real estates (up to 500 euros) or only from retirement income (up to 7,500 euros) plus income from land (up to 185,92 euros) plus income from a main residence and associated fixtures. The tax base is defined net of deductible expenses, such as social security and welfare contributions or donations to non profit organizations.

Table A2: Descriptive statistics – Self-employed workers

	Average value	Standard deviation	Count
<b>Panel A: Male</b>			
Married	.635	.481	1,892,849
Age	45.73	10.77	1,892,849
Foreign	.068	.253	1,892,849
Gross income	34,695.34	54,866.94	1,892,849
Taxable income	29,045.2	52,209.76	1,892,849
Spouse tax credit (recipient)	.187	.390	1,892,849
Spouse tax credit (amount)	123.84	263.76	1,892,849
Income tax	7,682.23	21,475.43	1,892,849
<b>Panel B: Female</b>			
Married	.648	.477	822,493
Age	45.87	11.16	822,493
Foreign	.071	.257	822,493
Gross income	25,049	34,918.3	822,493
Taxable income	21,185.89	33,079.84	822,493
Spouse tax credit (recipient)	.020	.143	822,493
Spouse tax credit (amount)	14.40	99.67	822,493
Income tax	5,184.49	13,022.9	822,493

*Note:* The table displays the descriptive statistics. The variables *Gross income*, *Taxable income*, *Spouse tax credit*, *Income tax* and *Spouse tax credit (amount)* are expressed in Euros.

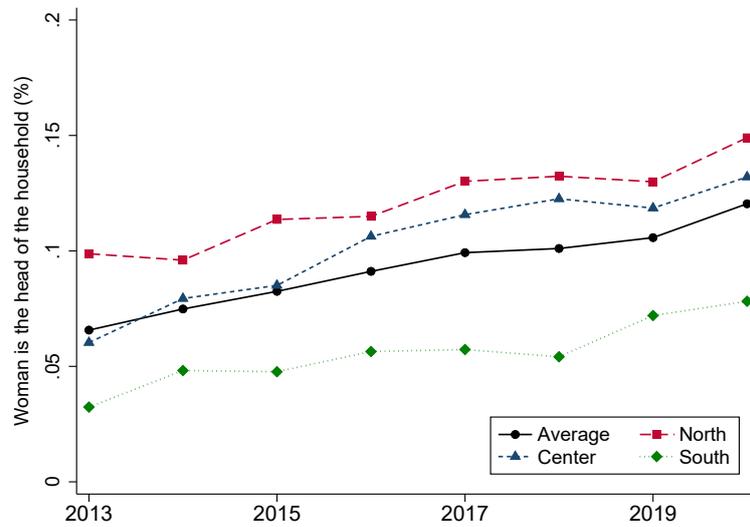
Table A3: Robustness to Polynomial Order

Polynomial order:	Bunching estimate for:	
	Women (1)	Men (2)
5	1.965*** (0.234)	-0.257 (0.252)
6	1.138*** (0.223)	-0.642*** (0.272)
7 (baseline)	1.238*** (0.247)	-0.008 (0.341)
8	1.197*** (0.251)	-0.111 (0.363)
9	1.433*** (0.244)	-0.224 (0.318)
10	1.497*** (0.287)	-0.116 (0.347)

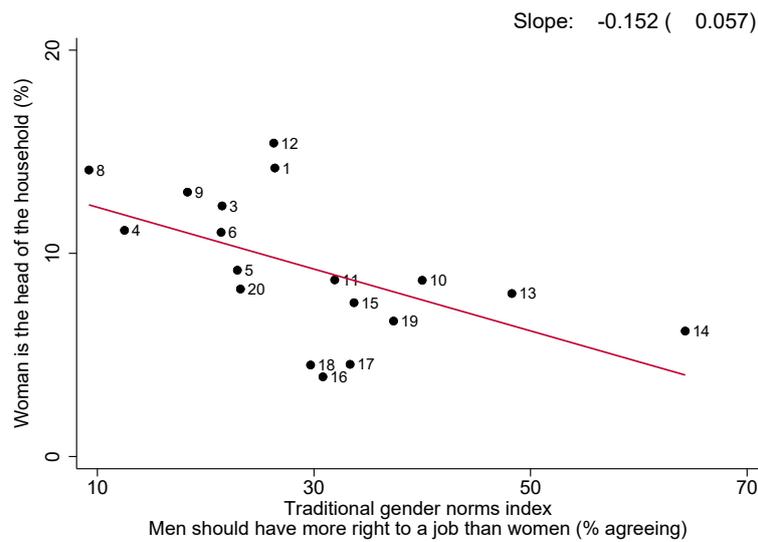
*Notes:* This table tests the sensitivity of our bunching estimate to the polynomial order's choice. We report bunching and standard error estimates with polynomial order ranging from 5 to 10 (including our baseline estimate that uses a seventh-degree polynomial).

Figure A1: Gender Norms and Wife Head of Household

A. Trends in Woman Head of Household



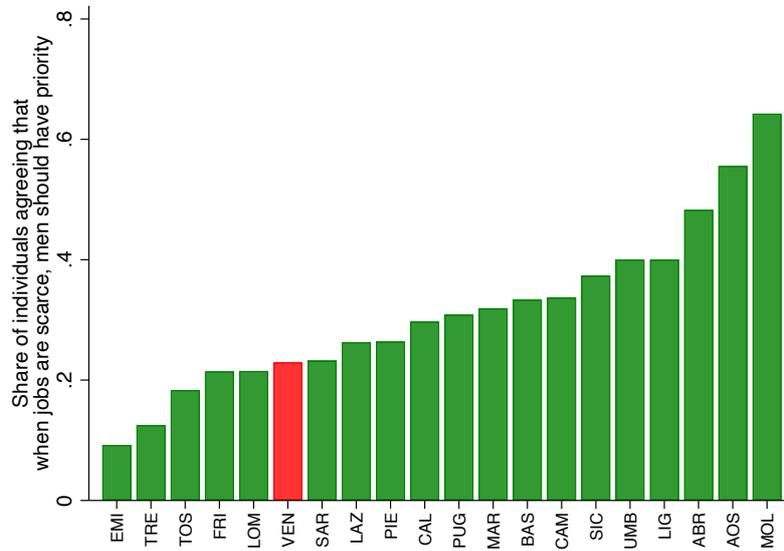
B. Gender Norms vs Women Head of Household



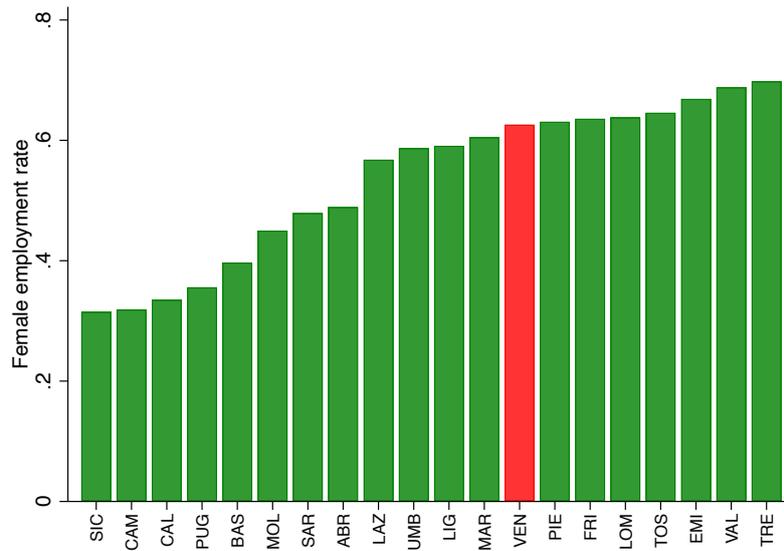
Notes: The top graph displays trends in the share of couples where the wife outearns her husband, as reported in a survey called Aspects of Daily Life (*Indagine Multiscopo sulle Famiglie: Aspetti della Vita Quotidiana*), provided by the Italian Institute of Statistics (ISTAT). We report separate series from couples living in the North of Italy (red squares), Center Italy (blue triangles), and South of Italy (green diamonds). The black solid line depicts the (unweighted) average. The bottom graph compares the region-specific share of couples where the woman leads the couple with the share of respondents agreeing that “men should have more right to a job than women”, using data from the 2017 European Values Study. Each point corresponds to the region-level average: 1 = Piedmont; 2 = Aosta Valley; 3 = Lombardy; 4 = Trentino Alto-Adige; 5 = Veneto; 6 = Friuli-Venezia Giulia; 7 = Liguria; 8 = Emilia-Romagna; 9 = Tuscany; 10 = Umbria; 11 = Marche; 12 = Lazio; 13 = Abruzzi; 14 = Molise; 15 = Campania; 16 = Puglia; 17 = Basilicata; 18 = Calabria; 19 = Sicily; 20 = Sardinia.

Figure A2: Gender Norms Index and Female Employment By Region

(a) Gender norms



(b) Female Employment



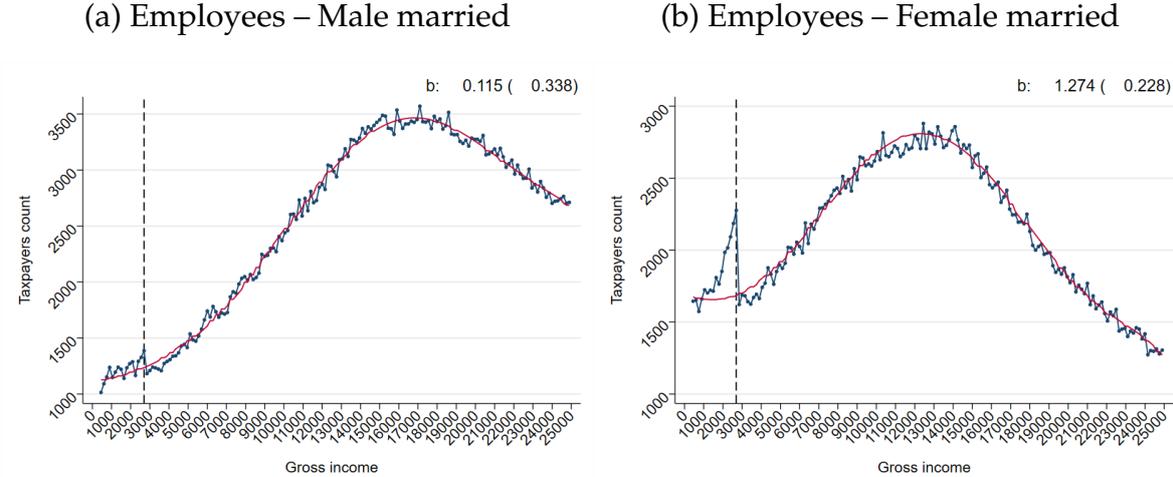
Notes: The top graph displays the region-level share of respondents agreeing that “when jobs are scarce, men should have priority” from the 2017 European Values Study. The bottom panel depicts female employment rate, using data from ISTAT. Each point corresponds to the region-level average: PIE = Piedmont; AOS = Aosta Valley; LOM = Lombardy; TRE = Trentino Alto-Adige; VEN = Veneto; FRI = Friuli-Venezia Giulia; LIG = Liguria; EMI = Emilia-Romagna; TUS = Tuscany; UMB = Umbria; MAR = Marche; LAZ = Lazio; ABR = Abruzzi; MOL = Molise; CAM = Campania; PUG = Puglia; BAS = Basilicata; CAL = Calabria; SIC = Sicily; SAR = Sardinia.

Figure A3: Take-Up Rate of Spouse Tax Credit By Income



Notes: This binscatter shows the take-up rate of spouse tax credit between married male and female as a function of the main earner's gross income. The sample includes all married taxpayers with an income above 5,000 Euros.

Figure A4: Bunching Responses to the Spouse Tax Credit - Excluding the credit recipients

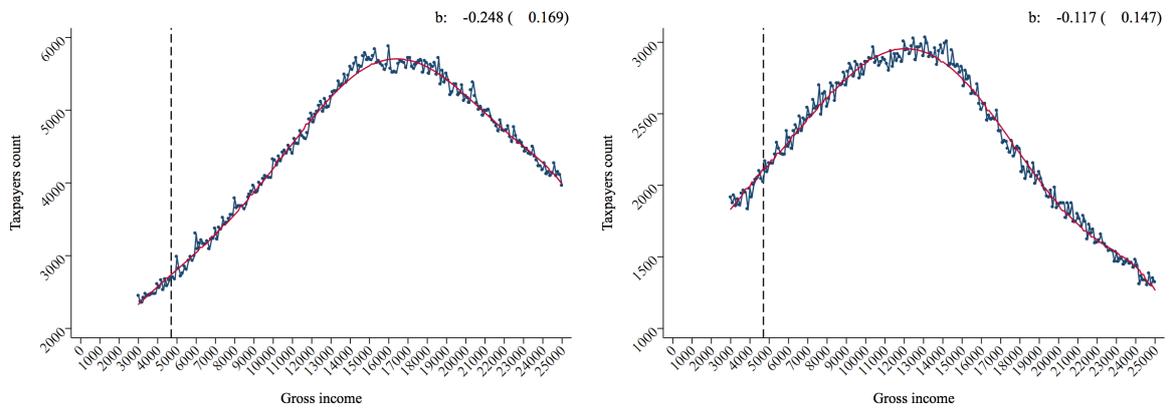


Notes: These figures present density distributions around the tax notch determining eligibility for the spouse tax credit (denoted by the dashed vertical line). Left-hand side graph focuses on married male taxpayers; right-hand side graph on married female taxpayers. In each graph, we report the number of taxpayers (by 150 euros bins) for gross income. The graphs also report counterfactual distributions (in red), bunching estimates and bootstrapped standard errors, computed as described in Section 3.2. Taxpayers who receive the spouse tax credit are excluded from the sample.

Figure A5: Bunching Responses to Tax Exemption Cutoff for Self-employees

(a) Men

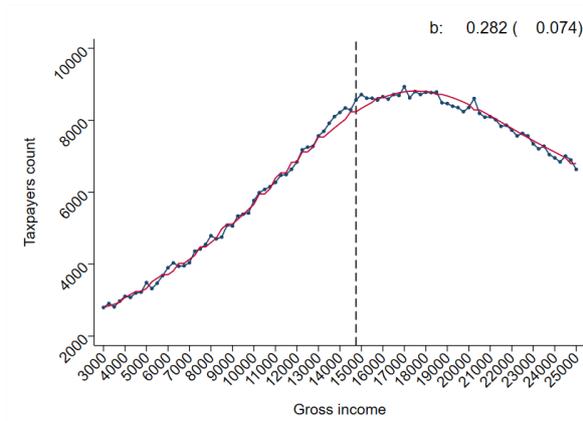
(b) Women



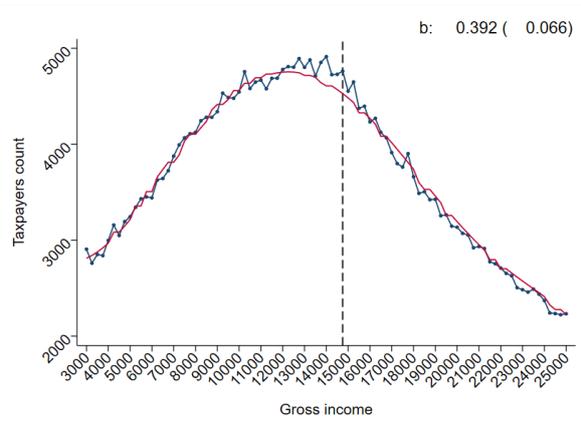
*Notes:* These figures present density distributions around the tax notch determining tax exemption for self-employees, 4,800 Euros (denoted by the dashed vertical line). Left-hand side graph focuses on male taxpayers; right-hand side graph on female taxpayers. In each graph, we report the number of taxpayers (by 100 euros bins) for gross income. The graphs also report counterfactual distributions (in red), bunching estimates and bootstrapped standard errors, computed as described in Section 3.2.

Figure A6: Bunching Responses to the First Tax Bracket Cutoff (15,000 Euros)

(a) Men

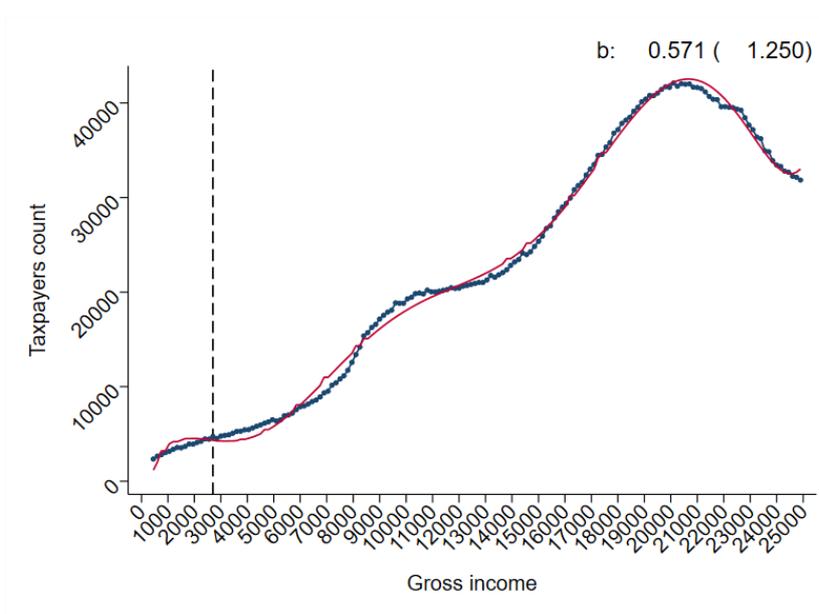


(b) Women



*Notes:* These figures present density distributions around the first tax bracket cutoff, 15,000 Euros (denoted by the dashed vertical line). Left-hand side graph focuses on male taxpayers; right-hand side graph on female taxpayers. In each graph, we report the number of taxpayers (by 150 euros bins) for gross income. The graphs also report counterfactual distributions (in red), bunching estimates and bootstrapped standard errors, computed as described in Section 3.2.

Figure A7: Bunching (placebo) – Employees – Married

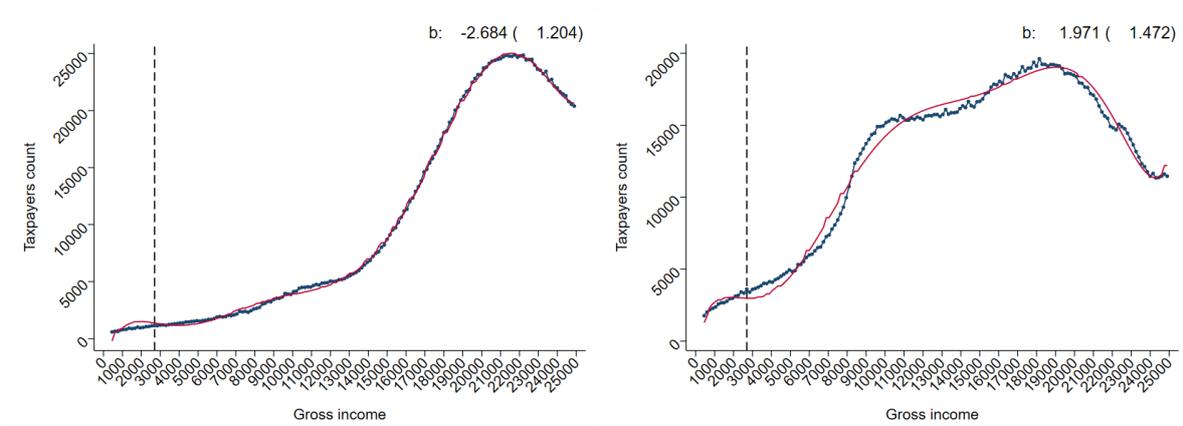


*Notes:* The figure presents density distributions around the tax notch determining eligibility for the spouse tax credit (denoted by the dashed vertical line). The sample includes all marrieds employees taxpayers. In the graph, we report the number of taxpayers (by 150 euros bins) for gross income. The graph also reports counterfactual distributions (in red), bunching estimates and bootstrapped standard errors, computed as described in Section 3.2.

Figure A8: Bunching (placebo) – Employees by gender

(a) Employees – Male married

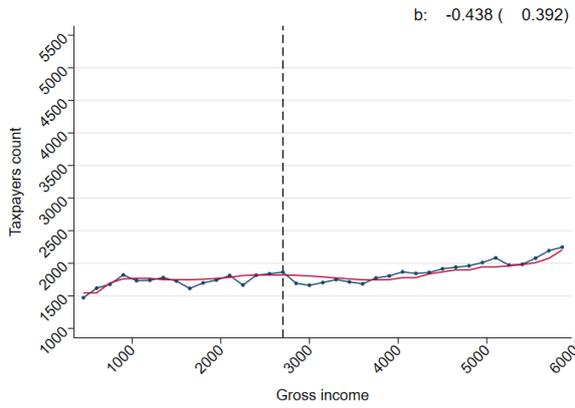
(b) Employees – Female married



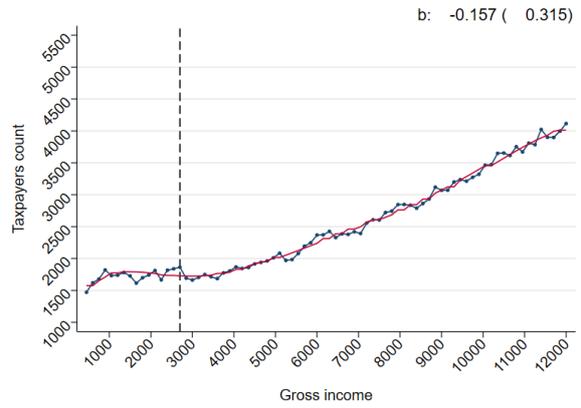
*Notes:* These figures present density distributions around the tax notch determining eligibility for the spouse tax credit (denoted by the dashed vertical line). The sample includes employees taxpayers: left-hand side graph focuses on married males; right-hand side graph on married females. In each graph, we report the number of taxpayers (by 150 euros bins) for gross income. The graphs also report counterfactual distributions (in red), bunching estimates and bootstrapped standard errors, computed as described in Section 3.2.

Figure A9: Bunching Responses - Male - Different Income Bandwidths

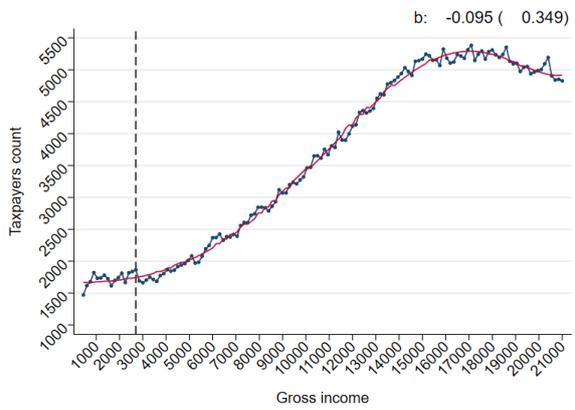
(a) Upper bound: 10th percentile



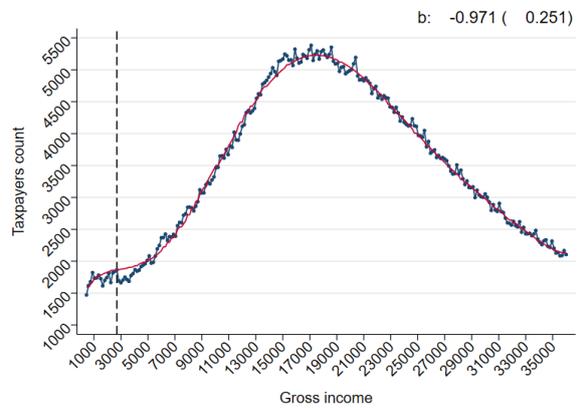
(b) Upper bound: 25th percentile



(b) Upper bound: 50th percentile



(b) Upper bound: 75th percentile

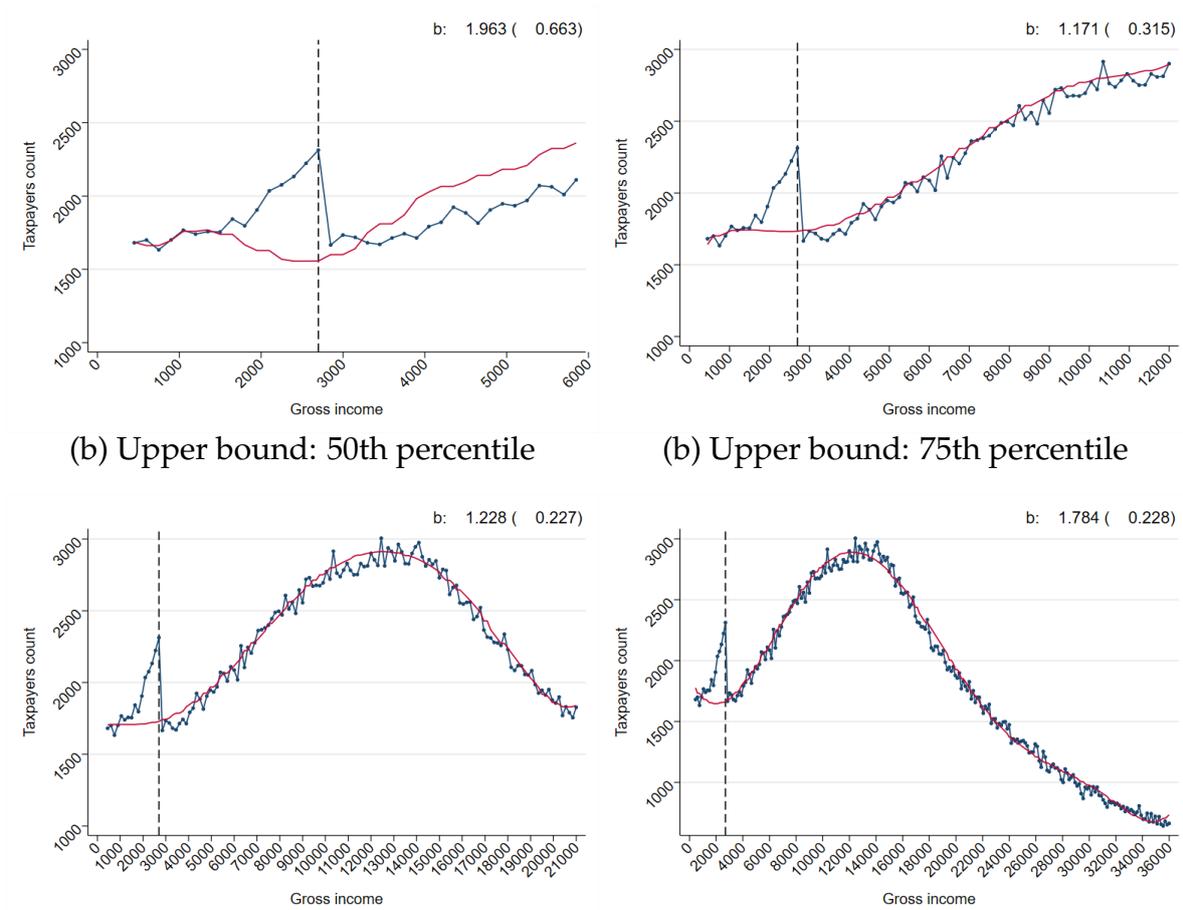


Notes: These figures present density distributions around the tax notch determining eligibility for the spouse tax credit for married men, changing the income upper bound (10th percentile –5,850 Euros–, 25th percentile –12,000 Euros–, 50th percentile –21,000 Euros–, 75th percentile –36,000 Euros–). In each graph, we report the number of taxpayers (by 150 euros bins) for gross income as well counterfactual distributions (in red), bunching estimates and bootstrapped standard errors, computed as described in Section 3.2.

Figure A10: Bunching Responses - Female - Different Income Bandwidths

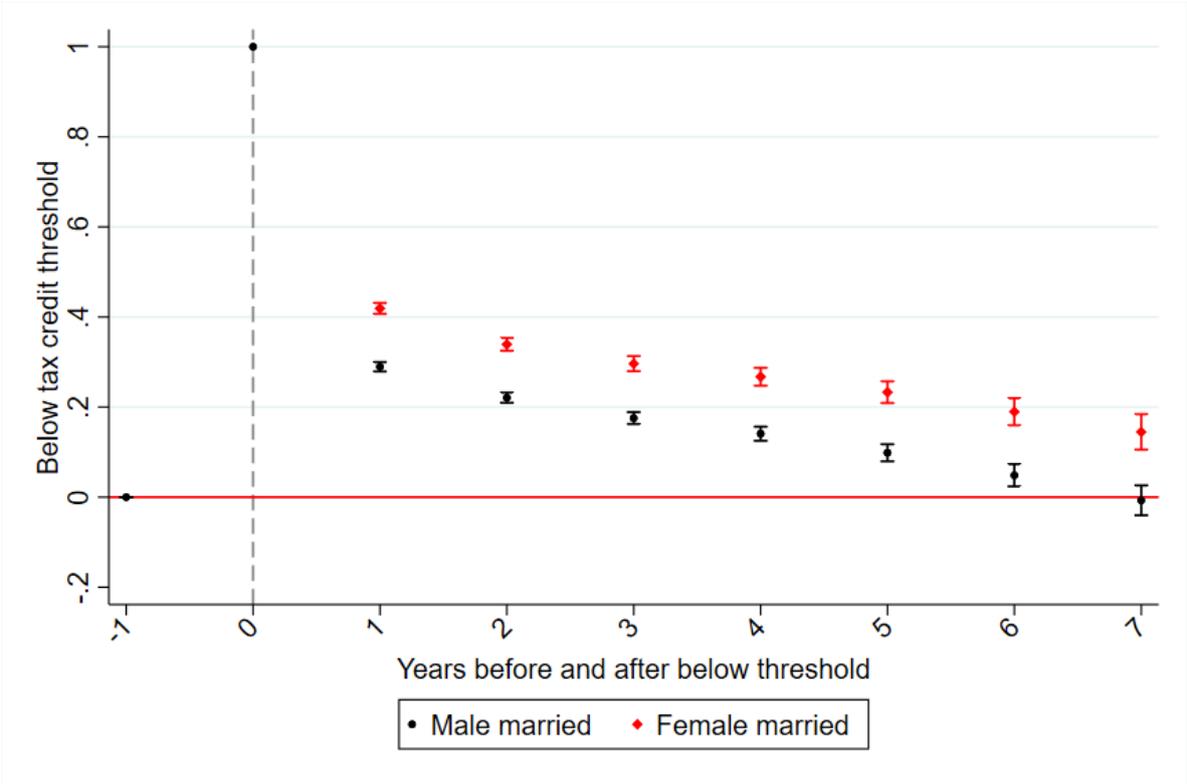
(a) Upper bound: 10th percentile

(b) Upper bound: 25th percentile



Notes: These figures present density distributions around the tax notch determining eligibility for the spouse tax credit for married women, changing the income upper bound (10th percentile –5,850 Euros–, 25th percentile –12,000 Euros–, 50th percentile –21,000 Euros–, 75th percentile –36,000 Euros–). In each graph, we report the number of taxpayers (by 150 euros bins) for gross income as well counterfactual distributions (in red), bunching estimates and bootstrapped standard errors, computed as described in Section 3.2.

Figure A11: Dynamic Responses to the Spouse Tax Credit: excluding concomitant events (marriage, childbirth)



Notes: This figure shows the probability of lingering in bunching, separately by gender. The figure reports the  $\beta_k$  coefficient estimate obtained from regressing equation (7), along with 95% (delimited by horizontal bars) and 90% (bold line) confidence intervals. Each coefficient estimate depicted in the graph tells us what is the probability that an individual will bunch again after  $k$  years since the first observed bunching episode (year 0 in the graph). We depict the  $\beta_k$  estimates for men (black circles) and women (red squares). Year -1 and year 0 estimates are mechanical. From the sample are excluded those taxpayers whose marriage or childbirth year coincides with the year of first bunching (i.e. marriage or childbirth happens one year before, the same year of one year after the first bunching episode).

## B Survey Evidence on Implications of Violating Gender Norms

This Appendix provides evidence on the implications of violating gender identity norms. We use data on married couples from 2013 to 2020 survey on Aspects of Daily Life (*Indagine Multiscopo sulle Famiglie: Aspetti della Vita Quotidiana*), provided by the Italian Institute of Statistics (ISTAT). For each couple, we collect information on who is the head of the household. In addition to basic demographics (region of residence, age, marital status, marriage tenure, education level) and labor market information (occupation, sector), the survey asks questions on a range of topics. We focus on two main groups of questions.

First, we retrieve information on life satisfaction, with questions focusing on both family, economic, friendship, and free-time satisfaction. For each question, respondents can choose answers on a scale of 1 (very happy) to 4 (very unhappy). We define a binary variable that simply takes value 1 if the respondent reports to feel “happy” or “very happy”. Second, we focus on their reported health status. We define a binary variable that takes value 1 if the respondents report to feel in very good or good health status.

To study whether the fact that the wife is the head of the household affects survey responses, we estimate the following linear probability model:

$$y_i = \beta \cdot 1(\text{WifeHeadHousehold}_i) + \gamma \cdot X_i + \delta \cdot C_{s(i)} + u_i \quad (\text{B1})$$

where  $y_i$  is the answer to a survey question by individual  $i$ . In the analysis, we examine wives’ and husbands’ responses separately. In this way, we can study whether it is the wife or the husband who dislikes the reversal of traditional gender identity norms.  $1(\text{WifeHeadHousehold})$  is a dummy taking value 1 in couples when wives are the head of the household.  $X_i$  contain both demographic and labor market controls (region fixed effects, year fixed effects, education groups, age groups, marriage tenure, civic status, occupation fixed effects, and sector fixed effects).  $C_{s(i)}$  collect demographic and labor market information on the spouse of the respondent. We cluster the standard errors at the region level.

[Table B1](#) presents our main results. We find that the violation of the male breadwinner model has important negative implications on couples’ life and economic satisfaction. Although we miss a plausibly exogenous source of variation in the probability of being the head of the household, we believe that this exercise provides three key suggestive results.

First, in couples where the wife’s income exceeds the husband’s, both the wife and the husband report to be less satisfied with their marriage (see panel A). Relative to

comparable couples where the husband is the main earner, couples where the wife outearns the husband are between 1 and 1.6 percentage points less likely to respond to feel “happy” or “very happy” with their marriage. In [Table B2](#), we also show that this effect spreads through the family: when the male breadwinner model fails, daughters are 2.1 percentage points less likely to feel “satisfied” or “very satisfied” about their family, while sons appear to be less responsive.

Second, husbands are more likely to report anxiety disorders when the male breadwinner model fails (panel D). In couples where the wife is the main earner, husbands are 1.7 percentage points more likely to report to suffer of anxiety disorders. This result is consistent with social psychology research stating that infringing of internalized rules generates apprehension and nervousness.

Finally, despite our empirical exercise is based on comparing couples with similar observable economic conditions, we find that wives report to be significantly less satisfied with the economic conditions of their family when they are the main earner in the couple (panel B).

As a robustness check, we test whether this pattern is also spuriously reflected in other outcomes, for which the relationship with violating the male breadwinner should be less obvious, if any. In panel C, we replicate the analysis on friends’ satisfaction. Reassuringly, we find negative but imprecisely estimated coefficient.

Table B1: Failure of Male Breadwinner Model and Couples' Outcomes

	(1)	(2)	(3)	(4)
A. Outcome: Marriage satisfaction				
Wife	-0.010*** (0.004)	-0.010*** (0.004)	-0.010*** (0.004)	-0.009** (0.004)
Husband	-0.016*** (0.004)	-0.015*** (0.004)	-0.015*** (0.004)	-0.015*** (0.004)
Observations	71,238	71,238	71,238	68,979
B. Outcome: Economic satisfaction				
Wife	-0.026*** (0.007)	-0.030*** (0.007)	-0.031*** (0.007)	-0.024*** (0.007)
Husband	-0.005 (0.008)	0.000 (0.008)	-0.006 (0.008)	-0.014* (0.008)
Observations	71,450	71,449	71,448	54,640
C. Outcome: Friends' satisfaction				
Wife	-0.004 (0.006)	-0.006 (0.005)	-0.006 (0.006)	-0.004 (0.006)
Husband	-0.012* (0.006)	-0.010* (0.006)	-0.010 (0.006)	-0.007 (0.007)
Observations	71,209	71,209	71,209	68,946
D. Outcome: Anxiety				
Wife	0.005 (0.008)	0.004 (0.008)	0.004 (0.008)	0.003 (0.008)
Husband	0.017*** (0.006)	0.015** (0.006)	0.016** (0.006)	0.012* (0.007)
Observations	38,501	38,501	38,500	37,294
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	Yes	Yes
Sector FE	No	Yes	Yes	Yes
Partner demographics	No	No	Yes	Yes
Partner occ and sec FE	No	No	No	Yes

*Note:* This table shows how failure of the male breadwinner model affect survey responses from wives (first row in each panel) and husbands (second row). In panel A, B, and C, the outcome variable is equal to 1 if the respondent reports to feel “happy” or “very happy”. In panel D, the outcome variable is equal to 1 if the respondent reports to suffer of anxiety “often” or “very often”. In each panel, we report the  $\beta$  estimate obtained from equation (B1) and region-level clustered standard errors. Each coefficient reports the difference in the outcome variable of interest between couples where the wife is the main earner (the male breadwinner model is violated) and couples where the husband is the main earner (male breadwinner model is satisfied). Therefore, each coefficient allows to test whether violating the male breadwinner model has significant implications.

Table B2: Failure of Male Breadwinner Model and Children's Outcomes

	Outcome variable:			
	Family satisfaction (1)	Economic satisfaction (2)	Friend satisfaction (3)	Anxiety (4)
Daughter	-0.021* (0.012)	0.002 (0.016)	-0.023* (0.012)	0.037** (0.017)
Observations	19,143	19,115	19,146	10,662
Son	-0.007 (0.009)	0.006 (0.018)	0.005 (0.008)	-0.010 (0.012)
Observations	23,480	23,500	23,491	13,004
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes

*Note:* This table shows how failure of the male breadwinner model affect survey responses from daughters (first row in each panel) and sons (second row). In columns (1)-(3), the outcome variable is equal to 1 if the respondent reports to feel "happy" or "very happy". In column (4), the outcome variable is equal to 1 if the respondent reports to suffer of anxiety "often" or "very often". In each panel, we report the  $\beta$  estimate obtained from equation (B1) and region-level clustered standard errors. Each coefficient reports the difference in the outcome variable of interest between children where their mother is the main earner (the male breadwinner model is violated) and children where their father is the main earner (male breadwinner model is satisfied). Therefore, each coefficient allows to test whether violating the male breadwinner model has significant implications.