

Foerster, Hanno; Obermeier, Tim; Schulz, Bastian

**Working Paper**

## Job Displacement, Remarriage, and Marital Sorting

IZA Discussion Papers, No. 17335

**Provided in Cooperation with:**

IZA – Institute of Labor Economics

*Suggested Citation:* Foerster, Hanno; Obermeier, Tim; Schulz, Bastian (2024) : Job Displacement, Remarriage, and Marital Sorting, IZA Discussion Papers, No. 17335, Institute of Labor Economics (IZA), Bonn

This Version is available at:

<https://hdl.handle.net/10419/305777>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*

DISCUSSION PAPER SERIES

IZA DP No. 17335

**Job Displacement, Remarriage, and  
Marital Sorting**

Hanno Foerster  
Tim Obermeier  
Bastian Schulz

SEPTEMBER 2024

## DISCUSSION PAPER SERIES

IZA DP No. 17335

# Job Displacement, Remarriage, and Marital Sorting

**Hanno Foerster**

*Boston College and IZA*

**Tim Obermeier**

*University of Leicester, CEP and IFS*

**Bastian Schulz**

*Aarhus University, IZA and CESifo*

SEPTEMBER 2024

Any opinions expressed in this paper are those of the author(s) and not those of IZA. Research published in this series may include views on policy, but IZA takes no institutional policy positions. The IZA research network is committed to the IZA Guiding Principles of Research Integrity.

The IZA Institute of Labor Economics is an independent economic research institute that conducts research in labor economics and offers evidence-based policy advice on labor market issues. Supported by the Deutsche Post Foundation, IZA runs the world's largest network of economists, whose research aims to provide answers to the global labor market challenges of our time. Our key objective is to build bridges between academic research, policymakers and society.

IZA Discussion Papers often represent preliminary work and are circulated to encourage discussion. Citation of such a paper should account for its provisional character. A revised version may be available directly from the author.

ISSN: 2365-9793

**IZA – Institute of Labor Economics**

Schaumburg-Lippe-Straße 5–9  
53113 Bonn, Germany

Phone: +49-228-3894-0  
Email: [publications@iza.org](mailto:publications@iza.org)

[www.iza.org](http://www.iza.org)

## ABSTRACT

---

# Job Displacement, Remarriage, and Marital Sorting\*

We investigate how job displacement affects whom men marry and study implications for marriage market matching theory. Leveraging quasi-experimental variation from Danish establishment closures, we show that job displacement leads men to break up if matched with low-earning women and to re-match with higher earning women. We use a general search and matching model of the marriage market to derive several implications of our empirical findings: (i) husbands' and wives' incomes are substitutes rather than complements in the marriage market; (ii) our findings are hard to reconcile with one-dimensional matching, but are consistent with multidimensional matching; (iii) a substantial part of the cross-sectional correlation between spouses' incomes arises spuriously from sorting on unobserved characteristics. We highlight the relevance of our results by simulating how the effect of rising individual-level inequality on between-household inequality is shaped by marital sorting.

**JEL Classification:** D1, J12, C78, D83, J31

**Keywords:** marriage market, sorting, search and matching, multidimensional heterogeneity

**Corresponding author:**

Bastian Schulz  
Aarhus University  
Department of Economics and Business Economics  
Fuglesangs Allé 4  
DK-8210 Aarhus V  
Denmark  
E-mail: [bastian.schulz@econ.au.dk](mailto:bastian.schulz@econ.au.dk)

---

\* We thank Jesper Bagger, Audra Bowlus, Luca Flabbi, Manolis Galenianos, Limor Golan, Nezh Guner, Kyle Herkenhoff, Christian Holzner, Philipp Kircher, Jeremy Lise, Lance Lochner, Guido Menzio, Giuseppe Moscarini, Theodore Papageorgiou, Robert Shimer, Rune Vejlin, participants at the NBER SI The Micro and Macro Perspectives of the Aggregate Labor Market, SED meetings, Barcelona Summer Forum Income Dynamics and the Family, SaM conference, and various seminar and conference audiences for helpful comments and suggestions. We are particularly grateful to Alexander Paul who participated in the early stages of this project. Kevin Choi and Catherine Lawlor provided excellent research assistance. Access to the Danish register data used in this study was provided by ECONAU, Aarhus University. The numerical results presented in this work were obtained via the Centre for Scientific Computing, Aarhus University. Bastian Schulz thanks the Aarhus University Research Foundation (Grant no. AUFF-F-2018-7-6), and the Dale T. Mortensen Centre at the Department of Economics and Business Economics, Aarhus University, for financial support.

# 1 Introduction

Who marries whom contributes to inequality. This idea, which goes back to [Becker \(1973\)](#), has motivated an extensive body of literature studying empirical patterns of marriage market sorting. A wide range of studies document cross-sectional correlations between spouses' characteristics, such as income and education (see, e.g., [Browning, Chiappori, and Weiss, 2014](#)), personality traits ([Becker, 1973](#); [Dupuy and Galichon, 2014](#)), measures of health ([Chiappori, Oreffice, and Quintana-Domeque, 2017a](#); [Guner, Kulikova, and Llull, 2018](#)) physical attractiveness ([Oreffice and Quintana-Domeque, 2010](#); [Chiappori, Oreffice, and Quintana-Domeque, 2012](#)), and wealth ([Fagereng, Guiso, and Pistaferri, 2022](#)).<sup>1</sup> However, less is known about the forces that give rise to these cross-sectional correlations. Consider the case of income: do individuals directly value a potential partner's income when making marriage decisions? Or does the observed positive correlation between spouses' incomes arise through other channels, for example, because marriage decisions are also based on other (potentially unobserved) characteristics that correlate with income?

In this paper, we offer novel empirical evidence and combine theory and data to study these questions. We estimate the effect of exogenous job displacements on men's marriage market transitions. To do so, we leverage variation from establishment closures in Denmark, and compare marriage market outcomes—such as breakup rates, which couples break up, couple formation rates, and which new couples form—between a treatment group of displaced men and a nondisplaced control group. This research design allows us to study how an adverse shock that reduces a person's long-term earnings potential influences their marriage market prospects. We leverage our empirical findings together with a general search and matching framework of the marriage market to derive broader implications for our understanding of marriage market matching and marital sorting.

Our empirical design compares over 72,000 displaced male workers with a nondisplaced control group. We follow the treatment and control groups over time, comparing their transitions into and out of marriages and cohabiting relationships. The research design relies on establishment closures as an exogenous source of variation to circumvent the endogeneity of individual job loss and voluntary quits. Our empirical results show that men who are displaced from their jobs (i) are more likely to experience a breakup, (ii) are particularly more likely to experience a breakup if matched with a low-earning partner, (iii) have an increased risk of remaining single post breakup, and (iv) are more likely to transition from a low-earning to a higher earning partner when re-matching, compared to the nondisplaced control group. We further show that finding (iv) is not driven by partners' labor supply choices, but is due to men matching with new partners who earn higher hourly wages. Additionally, we examine partner characteristics other than

---

<sup>1</sup>[Chiappori, Costa-Dias, and Meghir \(2020\)](#) establish two criteria that measures of sorting should satisfy, and show that the correlation coefficient satisfies both. [Chiappori et al. \(2020\)](#) further argue that measuring changes in sorting over time is challenging if the marginal distributions of the characteristic that people match on are non-constant. In this paper, we use correlation coefficients to measure sorting within a specific time period. As our analysis is focused on the underlying mechanisms that give rise to sorting in a given time period, we do not need to make comparisons over time.

labor earnings as outcomes and find no notable effects in terms of partners' age, education, or number of children. We conduct robustness checks that show that our results are not driven by displaced men moving to municipalities where women have higher earnings or where men are relatively scarce.

We use these empirical results to examine marriage market sorting and its underlying mechanisms. As shown in the seminal work of [Becker \(1973\)](#), marriage market sorting can be explained by complementarities in the match value from marriage. Intuitively, similar individuals mate if spouses' characteristics are complements, whereas dissimilar individuals mate if spouses' characteristics are substitutes.<sup>2</sup> Following this reasoning, various mechanisms have been proposed to explain why, empirically, couples tend to be sorted positively on income and education. For example, complementarities in home production hours ([Goussé, Jacquemet, and Robin 2017](#); [Chiappori, Salanié, and Weiss 2017b](#); [Calvo, Lindenlaub, and Reynoso 2024](#)), education homophily ([Chiappori, Costa-Dias, and Meghir 2018](#); [Chiappori, Iyigun, and Weiss 2009](#)), or market-purchased household public goods ([Lam 1988](#)). Other mechanisms imply substitutability of spouses' characteristics and, therefore, negative marriage market sorting. For example, substitutability in home production hours (leading to household specialization; see, e.g., [Becker 1973, 1981](#)) or risk sharing ([Chiappori et al., 2018](#); [Pilossoph and Wee, 2021](#)).<sup>3</sup> Thus, in standard (one-dimensional) models of marriage market matching, there is a tight link between complementarities in spouses' characteristics and cross-sectional patterns of marriage market sorting.<sup>4</sup>

We argue that our empirical results challenge this close relationship between observed sorting patterns and complementarities in spouses' characteristics. We show that our empirical findings (ii) and (iv)—that displaced men tend to transition away from low-earning partners and toward higher-earning partners—suggest a negative association between husbands' and wives' incomes, which is consistent with negative assortative matching (NAM) but inconsistent with positive assortative matching (PAM). By contrast, the observed positive correlation between matched spouses' incomes is in line with PAM but contradicts NAM. Under one-dimensional matching, our empirical findings (i)-(iv) and the positive correlation between spouses' incomes can be reconciled under neither PAM nor NAM. We demonstrate this formally within a general search and matching model of the marriage market, based on [Shimer and Smith \(2000\)](#).<sup>5</sup> Intuitively, when spouses' earnings are complements, the model generates a positive correlation between their incomes but predicts that, following job loss, men transition from high-earning to lower-earning partners (which contradicts our empirical evidence). In contrast, if spouses' incomes are substitutes, then the model predicts

---

<sup>2</sup>More technically, positive (negative) sorting arises if the match value from marriage is supermodular (submodular) (see, e.g., [Chiappori 2017](#)).

<sup>3</sup>These mechanisms are not mutually exclusive and some of the cited studies feature more than one of the described mechanisms.

<sup>4</sup>For example, [Calvo et al. \(2024\)](#) note that a strong role for household specialization is hard to reconcile with positive assortative matching.

<sup>5</sup>We choose a frictional dynamic model, as it provides a natural framework for jointly studying match formation and match dissolution, corresponding to our empirical results concerning the formation and dissolution of couples. For previous applications of the [Shimer and Smith \(2000\)](#) model to marriage markets see, e.g., [Wong \(2003a,b\)](#); [Jacquemet and Robin \(2013\)](#); [Goussé et al. \(2017\)](#); [Ciscato, Galichon, and Goussé \(2020\)](#); [Ciscato \(2021\)](#); [Holzner and Schulz \(2023\)](#).

that job loss leads men to transition from low-earning to higher-earning partners (in line with our empirical evidence) but generates a negative correlation between spouses' incomes, which is at odds with the data.<sup>6</sup>

To reconcile theory and evidence, we develop a multidimensional extension of the [Shimer and Smith \(2000\)](#) model. Under multidimensional matching, the link between complementarities in spouses' characteristics and marriage market sorting becomes more complex. For example, a positive correlation between spouses' incomes reflects not only sorting on income but also sorting on other characteristics that correlate with income (potentially including unobserved characteristics). As a consequence, a positive correlation between spouses' incomes may arise from sorting on correlates of income, even if sorting on income itself is negative (e.g., as this maximizes the gains from optimal division of labor in the household, as predicted by [Becker, 1973, 1981](#)).

We formally show that the multidimensional framework can jointly explain our empirical findings (i)-(iv) and the positive cross-sectional correlation between matched spouses' incomes. To show this, we define notions of PAM and NAM within the multidimensional framework. Sorting is defined dimension by dimension so that PAM can arise in one dimension, whereas NAM arises in another.<sup>7</sup> Our proposed model specification, which is consistent with the empirical facts, features negative sorting on income and positive sorting on other characteristics. This generates our empirical findings through the following simple mechanism: under negative sorting on income (holding other characteristics fixed), agents who experience job loss (and thus lose income) tend to transition away from low-earning spouses and toward higher-earning spouses. At the same time, positive sorting on other characteristics that correlate positively with income gives rise to the observed cross-sectional correlation between spouses' incomes. Thus, the positive correlation between spouses' incomes does not arise from sorting on income but is instead spuriously driven by sorting on other characteristics that correlate with income.<sup>8</sup>

We discuss several broader implications of our findings. First, our multidimensional framework offers a unifying perspective, allowing important roles for mechanisms that imply negative sorting on income (e.g., household specialization), and mechanisms that generate positive cross-sectional correlations between spouses' incomes. In our proposed multidimensional specification, holding other dimensions constant, sorting on incomes is negative, as predicted by [Becker \(1973, 1981\)](#). The positive cross-sectional correlation between spouses' incomes, on the other hand, is shaped by sorting on other dimensions, which may reflect education homophily (as in [Chiappori et al. 2009](#) and [Chiappori et al. 2018](#)) or sorting on home productivities (as in [Goussé et al. 2017](#); [Chiappori et al. 2017b](#) and [Calvo et al. 2024](#)). In our multidimensional

---

<sup>6</sup>We use the terms complements and substitutes loosely here. More precisely, sufficient conditions for PAM or NAM in the [Shimer and Smith \(2000\)](#) model involve the supermodularity or submodularity of the match value and the log-supermodularity or log-submodularity of its derivatives and cross-derivative.

<sup>7</sup>Similarly, [Lindenlaub and Postel-Vinay \(2023\)](#) define sorting dimension by dimension in a multidimensional search and matching model of the labor market.

<sup>8</sup>[Becker \(1981\)](#) describes this as a possible mechanism underlying the positive correlation between spouses' wages: "The positive correlation between wage rates of husbands and wives [...] may really be measuring the predicted positive correlation between a husband's wage rate (or his non-market productivity) and his wife's non-market productivity. Many unobserved variables, like intelligence, raise both wage rates and non-market productivity."

framework, these model mechanisms do not counteract each other but rather coexist and shape sorting patterns in different dimensions.

Second, we argue that our findings suggest a quantitatively meaningful role for sorting on both observed and unobserved characteristics. We decompose the cross-sectional correlation between matched spouses' incomes into components driven by sorting on income, sorting on other observed characteristics, and sorting on unobserved characteristics. Our results allow us to derive a lower bound for the share attributable to sorting on unobserved characteristics. Our findings imply that at least 42% of the positive regression coefficient obtained by regressing wives' income on husbands' income is explained by sorting on characteristics unobserved in our data (characteristics other than income, age, and education).

Third, to illustrate the relevance of our findings, we calibrate both a one-dimensional and a bidimensional specification of our framework. The bidimensional model matches both our main empirical findings and the positive correlation between spouses' incomes. In contrast, the one-dimensional model fails to match both at the same time. Furthermore, we simulate a counterfactual increase in individual income inequality in each calibrated model version and examine how the effect on between-household income inequality is shaped by marital sorting. The two models make markedly different predictions under the counterfactual. The one-dimensional model (which is at odds with our empirical evidence) predicts that marital sorting amplifies the increase in between-household income inequality; in contrast, the bidimensional model (which is consistent with our findings) predicts that marital sorting dampens the increase in between-household income inequality.

Our paper is related to several strands of literature. First, we contribute to a large body of literature that measures patterns of marriage market sorting (see, e.g., [Greenwood, Guner, Kocharkov, and Santos 2015](#); [Eika, Mogstad, and Zafar 2019](#); [Almar and Schulz 2024](#); [Almar, Friedrich, Reynoso, Schulz, and Vejlin 2024](#)) and interprets them using structural matching models (e.g., [Becker 1973, 1981](#); [Wong 2003a](#); [Choo and Siow 2006](#); [Goussé et al. 2017](#)). Cross-sectional patterns of sorting on income, wages, and education have generally been found to be positive (see, e.g., [Browning et al., 2014](#)), which has often been interpreted as evidence of complementarities in the match value from marriage (following the reasoning of [Becker 1973](#), likes mate if spouses' characteristics are complements).<sup>9</sup> Relatedly, it has been concluded that mechanisms that lead to complementarities in spouses' types (such as complementarities in home production hours, market-purchased household public goods, or education homophily) play a more important role than mechanisms that lead to substitutability in spouses' types (such as substitutability in home production hours or risk sharing). Our key innovation in this paper is to leverage exogenous variation from establishment closures to obtain novel evidence on marital sorting patterns that complements the correlational evidence from previous studies. We use our empirical evidence together with a structural model to show that our findings challenge the tight link between complementarities in spouses' characteristics and cross-sectional

---

<sup>9</sup>Several studies document further, that not only the raw correlations between spouses' wages (and labor incomes), but also partial correlations, when various other observed characteristics are held constant, are positive (see, e.g., [Becker, 1973](#)).



patterns of marital sorting. This link is at the core of one-dimensional models of the marriage market, which have been widely used to study marital matching. In sum, our findings offer a new perspective on the mechanisms that shape observed marital sorting patterns.

Second, we contribute to a more recent literature that explores multidimensional marriage market matching. While the majority of applied matching models are one-dimensional, multidimensional frictionless matching models of the marriage market have been explored by, e.g., [Chiappori et al. \(2012\)](#), [Dupuy and Galichon \(2014\)](#), [Adda, Pinotti, and Tura \(2024\)](#) and [Low \(2024\)](#). Multidimensional models with frictions have been studied in the context of labor markets (see, e.g. [Lindenlaub and Postel-Vinay 2021, 2023](#)), but have received less attention in the context of marriage market matching.<sup>10</sup> Our paper provides a novel multidimensional framework of the marriage market that extends the [Shimer and Smith \(2000\)](#) model. We build on previous multidimensional models of the marriage market, but extend them in several directions. While previous studies have focused on multidimensional frictionless matching and have not allowed for match dissolution, our framework includes search frictions, and, importantly, accounts for match formation as well as endogenous match dissolution. Additionally, our framework allows for multidimensional sorting on observed and unobserved characteristics, where observed and unobserved characteristics may be correlated. Furthermore, our new empirical evidence is consistent with multidimensional matching, while being inconsistent with standard one-dimensional models of the marriage market under PAM or NAM.

Third, we relate our findings to studies that use structural models to examine how marital sorting is affected by counterfactual changes in, e.g., the wage structure ([Fernández, Guner, and Knowles 2005](#), [Greenwood, Guner, Kocharkov, and Santos 2016](#), [Shephard 2019](#), [Calvo et al. 2024](#)), taxation ([Frankel 2014](#); [Bronson, Haanwinckel, and Mazzocco 2024](#); [Gayle and Shephard 2019](#)), social insurance ([Persson 2020](#), [Low, Meghir, Pistaferri, and Voena 2023](#); [Schulz and Siuda 2023](#)), or divorce laws ([Fernández and Wong 2016](#); [Reynoso 2024](#); [Calvo 2022](#)). Our counterfactual simulations illustrate that if the cross-sectional correlation between matched spouses' incomes directly arises from sorting on income, then marriage market sorting can be expected to amplify income inequality. However, if this correlation is a byproduct of sorting on other characteristics, then marriage market sorting may dampen income inequality. These findings highlight the relevance of understanding the mechanisms underlying observed marital sorting patterns for structural modeling and counterfactual simulations.

The remainder of our paper is structured as follows. Section 2 introduces our conceptual framework. Section 3 describes our data and empirical design. In Section 4, we present our empirical results. Section 5 describes how multidimensional matching reconciles theory with our empirical evidence. Section 6 explores broader implications of our findings and Section 7 concludes.

---

<sup>10</sup>A rare exception is the model by [Coles and Francesconi \(2019\)](#). In their model partnerships last forever and unobserved characteristics are not accounted for. [Lauermann, Nöldeke, and Tröger \(2020\)](#) argue that their proof of equilibrium existence extends to multidimensional settings.

## 2 Conceptual Framework

This section introduces a search-and-matching model of the marriage market. We build on the frictional version of the classical Beckerian assignment model developed by [Shimer and Smith \(2000\)](#), which features two-sided (one-dimensional) heterogeneity and transferable utility. The model serves as a conceptual framework and guides the development of our empirical strategy, which we outline in Section 3. Several empirical predictions emerge from this framework, and we subsequently test them in Section 4. Finally, we use the model to quantify the implications of our empirical results in Section 6.3.

### 2.1 Setup

We consider a two-sided matching environment populated by women, denoted by  $f$ , and men, denoted by  $m$ . Time is continuous and discounted at rate  $r$ . Women and men are fully characterized by their types,  $q_f \in Q_f$  and  $q_m \in Q_m$ , respectively. In general, we allow for multidimensional type spaces, assuming that  $Q_f = Q_m = \prod_{k=1}^K [q_k, \bar{q}_k]$ , where each dimension,  $k$ , of the Cartesian product represents a distinct type attribute. We will clearly indicate whenever we examine the special case of one-dimensional matching ( $K = 1$ ) or the more general multidimensional case ( $K > 1$ ). Under one-dimensional matching, agent types are summarized by a single attribute (e.g., income or education), whereas multidimensional matching allows for various attributes that may or may not be correlated.

We assume random search. Denote by  $G_f$  and  $G_m$  the cumulative distribution functions (CDFs) of single women's and men's types, respectively.<sup>11</sup> At rate  $\lambda_f$ , a single woman meets a single man drawn from  $G_m$ . Conversely, at rate  $\lambda_m$ , a single man meets a single woman, drawn from  $G_f$ . We follow [Shimer and Smith \(2000\)](#) and assume that the meeting rates for men and women are proportional to the mass of singles of the other gender, i.e.,  $\lambda_f = \lambda \int dG_m(q_m)$  and  $\lambda_m = \lambda \int dG_f(q_f)$ , respectively, where  $\lambda$  is a common Poisson rate. Upon meeting, female and male agents observe each other's types and jointly decide whether to accept and form a match or to reject and continue the search for a partner.

### 2.2 Flow Utilities

Single agents' flow value depends on their type  $q_g$  ( $g \in \{f, m\}$ ), and is given by the flow utility function  $u_g^0(q_g)$ .<sup>12</sup> Matched women and men enjoy flow utilities  $u_f^1(q_f, q_m)$  and  $u_m^1(q_f, q_m)$ , where  $u_f^1(q_f, q_m)$  is the flow utility of a type  $q_f$  woman matched with a type  $q_m$  man (and vice versa for men). The flow match value,  $f(q_f, q_m)$ , equals the sum of the matched partners' individual flow utilities,

$$f(q_f, q_m) = u_f^1(q_f, q_m) + u_m^1(q_f, q_m). \quad (1)$$

<sup>11</sup>Note that  $G_f$  and  $G_m$  are equilibrium outcomes, i.e., endogenous objects.

<sup>12</sup>Model objects with superscript 0 refer to singles, whereas objects with superscript 1 refer to matched agents.

### 2.3 Bellman Equations and Matching

A model agent's decision problem is summarized by two Bellman equations. Denote by  $\mathcal{M}(q_g)$  the matching set of a model agent of type  $q_g$ , i.e.,  $q_f \in \mathcal{M}(q_m)$  and  $q_m \in \mathcal{M}(q_f)$  if type  $q_f$  women and type  $q_m$  men agree to match upon meeting. It follows that the value of being a type  $q_m$  single man is given by

$$rV_m^0(q_m) = u_m^0(q_m) + \lambda_m \int_{\mathcal{M}(q_m)} (1 - \mu_f) S(q_f, q_m) dG_f(q_f), \quad (2)$$

where  $(1 - \mu_f) S(q_f, q_m)$  is the share of the marital surplus that type- $q_m$  men receive in a match with a type- $q_f$  woman, given the female Nash bargaining power  $\mu_f$ . This Bellman equation states that the value of being single is determined by the flow utility of singlehood and the option value of matching with a partner.

The value for a type- $q_m$  man of being matched with a type- $q_f$  woman is

$$rV_m^1(q_f, q_m) = u_m^1(q_f, q_m) + t_m + \delta(V_m^0(q_m) - V_m^1(q_f, q_m)), \quad (3)$$

where  $\delta$  is the exogenous separation rate.  $t_m$  denotes the intra-household utility transfer, which may be positive or negative.<sup>13</sup>

Given these Bellman equations, the marital surplus is defined as

$$S(q_f, q_m) = V_m^1(q_f, q_m) + V_f^1(q_f, q_m) - V_m^0(q_m) - V_f^0(q_f). \quad (4)$$

The transferable utility assumption entails that the marital surplus can be distributed between spouses without frictions. Couples therefore match upon meeting if (and only if) the marital surplus is weakly positive (i.e.  $S(q_f, q_m) \geq 0$ ). The transfer ensures that both spouses benefit relative to remaining single. The model is closed by assuming that the spouses share the marital surplus by Nash bargaining, which implies that transfers are set such that the wife receives a share  $\mu_f S(q_f, q_m)$  of the marital surplus while the husband receives  $(1 - \mu_f) S(q_f, q_m)$  (see Appendix D.1 for details).

### 2.4 Equilibrium and Sorting

For the one-dimensional case ( $K = 1$ ), [Shimer and Smith \(2000\)](#) prove the existence of an equilibrium that satisfies: 1. *individually optimal behavior*: every agent maximizes her expected payoff, taking all other agents' strategies as given. 2. *steady-state*: match creation equals match destruction for each agent type (i.e., for all  $q_f$  and all  $q_m$ ). [Shimer and Smith \(2000\)](#) characterize sorting by defining the following notions of PAM and NAM, which generalize the corresponding definition for the frictionless case by [Becker \(1973\)](#).<sup>14</sup>

<sup>13</sup>The values of being a single woman or type- $q_f$  women matched with a type- $q_m$  man are defined analogously to (2) and (3). Transfers are constraint to be net-zero, i.e.,  $t_m = -t_f$ .

<sup>14</sup>Note that as matching is symmetric,  $q_f \in \mathcal{M}(q_m)$  is equivalent to  $q_m \in \mathcal{M}(q_f)$ . The definitions of PAM and NAM thus imply that the respective relationships with  $q_m$  and  $q_f$  interchanged also hold.

**Definition 1.** Consider  $q'_f < q''_f, q'_m < q''_m$ .

There is PAM if:  $q''_f \in \mathcal{M}(q'_m)$  and  $q'_f \in \mathcal{M}(q''_m) \Rightarrow q'_f \in \mathcal{M}(q'_m)$  and  $q''_f \in \mathcal{M}(q''_m)$

There is NAM if:  $q'_f \in \mathcal{M}(q'_m)$  and  $q''_f \in \mathcal{M}(q''_m) \Rightarrow q''_f \in \mathcal{M}(q'_m)$  and  $q'_f \in \mathcal{M}(q''_m)$ .

Intuitively, under PAM, whenever two couples,  $(q'_f, q'_m)$  and  $(q''_f, q''_m)$ , can form more positively sorted matches by trading partners, they are willing to do so. By implication, higher- $q_m$  men match on average with higher- $q_f$  women in any PAM equilibrium. That is,  $\mathbb{E}[q_f|q_m]$  is weakly increasing in  $q_m$  in the population of matched couples. In contrast, higher- $q_m$  men will match on average with lower- $q_f$  women in any NAM equilibrium. That is,  $\mathbb{E}[q_f|q_m]$  is weakly decreasing in  $q_m$  in the population of matched couples. As a consequence, for the correlation between matched partners' types the following holds:

$$\text{PAM} \Rightarrow \text{Corr}(q_f, q_m) \geq 0, \quad (5)$$

$$\text{NAM} \Rightarrow \text{Corr}(q_f, q_m) \leq 0. \quad (6)$$

Using (5) and (6), it is possible to use observed cross-sectional correlations between matched spouses' attributes to draw conclusions about marital sorting patterns. Specifically, under one-dimensional matching,  $\text{Corr}(q_f, q_m) < 0$  is inconsistent with PAM, while  $\text{Corr}(q_f, q_m) > 0$  is inconsistent with NAM. Under the common assumption that agent types map (one-to-one) into income or education levels, the widely documented positive correlations between spouses' income and education levels have been interpreted in the literature as evidence that refutes NAM and supports PAM.

## 2.5 Job Loss and Marriage Market Matching

To link our conceptual framework to the effects of job loss that we estimate in our data, we maintain the assumption of one-dimensional matching ( $K = 1$ ) and interpret job displacement as a permanent unexpected reduction of an agent's type. Additionally, we assume that agent types map into labor incomes by an increasing one-to-one function.<sup>15</sup> Our interpretation is consistent with extensive empirical evidence on the long-term effects of job loss, e.g., wage scarring.<sup>16</sup> Formally, we assume that a man of type  $q_m$  who is displaced from his job suffers a permanent type reduction to  $q_m - d$ , where  $d > 0$ .

We use our conceptual framework to derive predictions regarding the effects of job displacement that we identify in our empirical analysis: consider two groups of men (a "treatment group" and a "control group"), observed at two points in time,  $t_0$  and  $\tau > t_0$ . Suppose that men in both groups are matched with a female partner in period  $t_0$ . Men in the treatment group are displaced from their jobs in  $t_0$ , whereas men in the control group are not displaced between  $t_0$  and  $\tau$ . Formally,  $q_m(\tau) = q_m(t_0) - d$  for the treated and

<sup>15</sup>This assumption allows for agent types mapping (one-to-one) into other agent characteristics that also deteriorate upon job displacement (such as health).

<sup>16</sup>See our own empirical results in Section 4, as well as previous studies (e.g., Jacobson, LaLonde, and Sullivan, 1993; Sullivan and von Wachter, 2009).

$q_m(\tau) = q_m(t_0)$  for the control group. Throughout, we impose that the treatment group is small (i.e., of measure zero) so that job displacements impact the displaced agents, but do not induce a transition to a new steady-state equilibrium.

We denote by  $D$  a treatment indicator, which equals 1 for the (displaced) treatment group and 0 for the (nondisplaced) control group. The CDFs of men's types in the treatment group and the control group are denoted by  $F(q_m|D = 1)$  and  $F(q_m|D = 0)$ , respectively. We further denote by  $D_B$  an indicator for whether a man experiences a breakup from his  $t_0$ -partner between  $t_0$  and  $\tau$ .  $D_R$  denotes an indicator for whether he rematches with a new partner between  $t_0$  and  $\tau$ .

In our empirical analysis, we estimate the following effects of job displacement.

1. The impact of job displacement on breakup risk:

$$\gamma_B = P(D_B = 1|D = 1) - P(D_B = 1|D = 0).$$

2. The impact of job displacement on which male and female types experience a breakup:

$$\begin{aligned}\gamma_{q_m|B} &= \mathbb{E}[q_m(t_0)|D_B = 1, D = 1] - \mathbb{E}[q_m(t_0)|D_B = 1, D = 0], \\ \gamma_{q_f|B} &= \mathbb{E}[q_f(t_0)|D_B = 1, D = 1] - \mathbb{E}[q_f(t_0)|D_B = 1, D = 0].\end{aligned}$$

3. The impact of job displacement on the risk of remaining single after a breakup:

$$\gamma_{R=0|B} = P(D_R = 0|D_B = 1, D = 1) - P(D_R = 0|D_B = 1, D = 0).$$

4. The impact of job displacement on the expected female type with which a man rematches after a breakup:

$$\gamma_{\Delta q_f|R} = \mathbb{E}[q_f(\tau) - q_f(t_0)|D_R = 1, D_B = 1, D = 1] - \mathbb{E}[q_f(\tau) - q_f(t_0)|D_R = 1, D_B = 1, D = 0].$$

Note that both a treatment margin and a selection margin contribute to  $\gamma_{\Delta q_f|R}$ ,  $\gamma_{q_m|B}$ ,  $\gamma_{q_f|B}$  and  $\gamma_{R=0|B}$ . First, job displacement may affect which types of men experience a breakup. Second, for a given man, job displacement may have an effect on his propensity to find a partner or to rematch with a specific  $q_f$ -type. We leverage our conceptual framework to derive and test predictions regarding both the treatment and the selection margin. Based on our conceptual framework, we show that the following relationships between marriage market sorting and the described effects of job displacement hold:<sup>17</sup>

**Proposition 1.** *Consider the described matching environment in steady-state equilibrium.*

*Under either PAM or NAM:*

1. *Job displacement increases the breakup risk:  $\gamma_B \geq 0$ .*

---

<sup>17</sup>For proofs and derivations see Appendix A.

2. Job displacement may increase or decrease the probability of staying single:

$\gamma_{R=0|B}$  may be positive or negative.

Under PAM:

3.-a Job displacement leads men to rematch with women of lower type:  $\gamma_{\Delta q_f|R} \leq 0$ .

4.-a The association between job displacement and partner type is bounded above:  $\gamma_{\Delta q_f|R} \leq \bar{\gamma}_{\Delta q_f|R}$ .

The upper bound is given by

$$\bar{\gamma}_{\Delta q_f|R} = - \int \int_0^d \frac{\partial \mathbb{E}[q_f|q_m]}{\partial q_m} \Big|_{q_m=q-x} dx dF(q|D_R = 1, D_B = 1, D = 1) \leq 0.$$

5.-a If  $F(q_m|D_B = 1, D = 1) \leq F(q_m|D_B = 1, D = 0)$  holds additionally, then, on average, women from whom displaced men separate are of higher type than women from whom nondisplaced men separate:  $\gamma_{q_f|B} \geq 0$ .

Under NAM:

3.-b Job displacement leads men to rematch with women of higher type:  $\gamma_{\Delta q_f|R} \geq 0$ .

4.-b The association between job displacement and partner type is bounded below:  $\gamma_{\Delta q_f|R} \geq \underline{\gamma}_{\Delta q_f|R}$ .

The lower bound is given by

$$\underline{\gamma}_{\Delta q_f|R} = - \int \int_0^d \frac{\partial \mathbb{E}[q_f|q_m]}{\partial q_m} \Big|_{q_m=q-x} dx dF(q|D_R = 1, D_B = 1, D = 1) \geq 0.$$

5.-b If  $F(q_m|D_B = 1, D = 1) \geq F(q_m|D_B = 1, D = 0)$  holds additionally, then, on average, women from whom displaced men separate are of lower type than women from whom nondisplaced men separate:  $\gamma_{q_f|B} \leq 0$ .

Relationships (3.-a) and (3.-b) show that under PAM or NAM marriage market sorting pins down the sign of the association between job displacement and partner type,  $\gamma_{\Delta q_f|R}$ . Moreover, relationships (4.-a) and (4.-b) show that  $\gamma_{\Delta q_f|R}$  is bounded away from zero by bounds that are determined by the slope of  $\mathbb{E}[q_f|q_m]$  in  $q_m$ , which adds an additional, empirically testable implication.

In Sections 3 and 4, we leverage quasi-experimental variation from plant closures to obtain empirical estimates of  $\gamma_B$ ,  $\gamma_{q_m|B}$ ,  $\gamma_{q_f|B}$ ,  $\gamma_{\Delta q_f|R}$ , and  $\gamma_{R=0|B}$ . We compare these estimates to the relationships implied by Proposition 1 to confront the described marriage market matching framework with empirical evidence.

### 3 Empirical Strategy

Our research design compares 72,667 male workers who lose their jobs due to establishment closures with a control group of workers who are similar in terms of observable characteristics but not affected by an establishment closure during our sample period. The following subsections describe our data, the definitions of establishment closures and job displacement, the matching procedure by which we select a control group, and the main empirical specifications that we estimate in Section 4.

### 3.1 Data

Our empirical analysis relies on Danish register data covering the entire population living in Denmark between 1980 and 2007.<sup>18</sup> The data are drawn from tax and social security records and include individual-level information on a range of demographics, as well as employment status, labor income, occupation, work hours, identifiers of the firm and establishment the individual is employed at, marital histories, and children. In particular, the data record whether an individual is married or in a cohabiting relationship, and provide an identifier of the individual's spouse or cohabiting partner. Cohabiting couples are defined as two opposite-sex individuals who share the same address, exhibit an age difference of less than 15 years, have no family relationship, and do not share housing with adults other than their partner.<sup>19</sup>

### 3.2 Establishment Closures

We define a closing establishment as one that stops operating, i.e., completely sheds its workforce within three years.<sup>20</sup> The treatment year is defined as the first year in which a closing establishment sheds 10% or more of its workforce. The rationale behind this definition is that layoffs occurring after 10% or more of an establishment's workforce has already been laid off are likely anticipated by the remaining workers. We exclude establishments with fewer than 5 employees in the treatment year. We identify 23,913 closing establishments in our data that satisfy these criteria. The mean closing establishment in our data employs 55 workers in the treatment year.

### 3.3 Treatment and Control Group

**Treatment group** We select our treatment group from men who are employed at a closing establishment during the treatment year and have at least three years of tenure.<sup>21</sup> Additionally, we restrict the treatment group to men who are 28–48 years old in the treatment year and who were married or in a cohabiting relationship three years prior to the treatment year.<sup>22</sup> Men who are employed at the same establishment as their spouse or cohabiting partner are excluded from the treatment sample. Our treatment group consists of 72,667 individuals who meet these criteria.

---

<sup>18</sup>Our sample ends in 2007 due to a change in the definition of family types in the Danish registers.

<sup>19</sup>This is the official definition of cohabiting couples used by Statistics Denmark. For previous studies that have relied on this definition see, (e.g., Svarer, 2004; Datta Gupta and Larsen, 2007; Datta Gupta and Larsen, 2010; Bruze, Svarer, and Weiss, 2015). Our data do not allow us to identify cohabiting same-sex couples. Therefore, we do not include same-sex couples in our analysis. Same-sex marriage has been legal in Denmark since 2012.

<sup>20</sup>By focusing on establishment closures instead of a broader notion of establishment-level employment reduction (often referred to as "mass-layoffs"), we minimize selection problems that may occur if employment reductions are influenced by worker performance and ability (see, e.g., Eliason and Storrie 2006).

<sup>21</sup>We repeated our empirical analysis for displaced women. In contrast to men, women experience a much less persistent earnings loss in our sample. We find a statistically insignificant effect on breakup rates in couples where the female partner is displaced. This is consistent with previous findings by Huttunen and Kellokumpu (2016) and Eliason (2012), who document that men's displacement leads to a statistically significant increase in relationship dissolution risk, but find no significant effect for displaced women. The effects of job displacement on which couples separate, the risk of staying single post breakup, and which new couples form are also insignificant for displaced women.

<sup>22</sup>Note that in our analysis, we consider an event time window ranging from five years prior to ten years after establishment closure. Within this time window the considered men are 23–58 years old.



**Coarsened exact matching to select control group** To select a control group, we rely on matched sampling from men who, during our sample period, were never employed at an establishment within three years of its closure. We apply the same sample restrictions on age, tenure, and relationship status and exclude men coworking with their partner, as in the treatment group. We implement a coarsened exact matching (CEM) algorithm on the resulting pool of individuals. For each treated individual, the algorithm selects one control individual who, in the treatment year, provides an exact match on various observed characteristics (Iacus, King, and Porro, 2012, 2019). To make exact matching feasible in all cases, the observables we match on are coarsened into discrete bins (except for those already discrete). The CEM algorithm then matches each treated individual with a control individual whose characteristics fall in the same bin for each observable.<sup>23</sup> The observed characteristics that our CEM algorithm matches on are marital status (single, cohabiting, married, divorced), age, children (binary indicator), calendar year, occupation (6 categories), industry (9 groups), establishment size quintiles, and tenure quintiles. We match treatment and control group with respect to each of these variables three years before establishment closure, except for establishment size quintiles, which we match five years before closure.<sup>24</sup> Our empirical analysis draws on the combined sample of 72,667 displaced men in the treatment group and the same number of men in the control group. For men in the control group, we refer to the year in which the matched treatment individual is displaced as “the year of placebo displacement”.

**Summary statistics** Table B.1 reports summary statistics in the year before (actual or placebo) displacement for the treatment group and the control group. The average displaced worker is 38 years old with 12.6 years of education, corresponding approximately to a high school or vocational degree. In the year before displacement actual and placebo displaced workers earn annual salaries of 326,247 DKK in the treatment group and 324,898 DKK in the comparison group.<sup>25</sup> Their married or cohabiting partners are on average 36 years old, with 12.2 (treatment group’s partners) and 12.3 (control group’s partners) years of education, and earn annual salaries of 177,682 DKK (treatment group’s partners) and 178,891 DKK (control group’s partners). The similarity between treatment and control group is not entirely mechanical as our coarsened exact matching relies on variables three and five years before actual/placebo displacement. Moreover, Table B.1 includes several variables that we do not match on (e.g., labor income as well as partner’s, age, education, and labor income).

---

<sup>23</sup>Coarsened exact matching has favorable statistical properties in finite samples compared with methods such as propensity score matching (see Iacus et al., 2012), and the appeal of being straightforward to interpret. See Azoulay, Graff Zivin, and Wang (2010) and Jäger and Heining (2022) for previous applications.

<sup>24</sup>For matching on establishment size, we move two years further away from establishment closure, as this variable begins to differ early between treatment group and control group.

<sup>25</sup>Throughout, all money measures are CPI adjusted to 2004 DKK.



### 3.4 Estimating Equations

**Unconditional difference-in-differences specification** We estimate the effect of job displacement on labor market and marriage market outcomes using the following difference-in-differences specification:

$$Y_{it} = \alpha + \sum_{\tau=-5}^{10} \psi_{\tau} \mathbb{1}\{t = \tau\} + \sum_{\tau=-5}^{10} \phi_{\tau} D_i \mathbb{1}\{t = \tau\} + \phi_D D_i + e_{it}, \quad (7)$$

where  $Y_{it}$  denotes the outcome  $Y$  for individual  $i$  in year  $t$  relative to the year of actual or placebo displacement.  $D_i$  is an indicator of whether individual  $i$  is in the treatment group and  $e_{it}$  is the residual error term. We normalize  $\psi_{-3} = \phi_{-3} = 0$ . The coefficients of interest,  $\phi_{\tau}$ , capture the effect of job displacement on the treatment group relative to the control group, at event time  $\tau$ . We do not include calendar year fixed effects in (7) because calendar time is exactly balanced between treatment and control group, as it is one of the variables we match on in the coarsened exact matching procedure. The specification allows for time invariant differences between the treatment and control groups, which are absorbed by  $\phi_D$ . The variation we leverage to estimate  $\phi_{\tau}$  is differential variation over event time (relative to actual or placebo job displacement) in the treatment group relative to the control group. The key identifying assumption is that in the absence of job displacement, treatment and control group would have been on parallel trends.

**Match-specific difference-in-differences specification** To estimate how job displacement impacts matching patterns, we use the following match-specific difference-in-differences specification.<sup>26</sup> We run this specification on a sample of partners  $j$  who are matched with a treatment or control group individual at some point during the even-time window  $t = -5, \dots, 10$ .<sup>27</sup>

$$Y_{jt} = \alpha + \alpha_{t_M > 0} \mathbb{1}\{t_M(i, j) > 0\} + \phi_{t_M > 0} D_{i(j)} \mathbb{1}\{t_M(i, j) > 0\} + \phi_D D_{i(j)} + e_{jt}. \quad (8)$$

where,  $Y_{jt}$  denotes the outcome  $Y$  for individual  $j$  in year  $t$  relative to the year of actual or placebo displacement.  $D_{i(j)}$  is an indicator for whether individual  $i(j)$ , who was matched with individual  $j$ , is in the treatment group.<sup>28</sup>  $t_M(i, j)$  denotes the time relative to actual or placebo displacement at which the match between  $i$  and  $j$  is formed. I.e.,  $\mathbb{1}\{t_M(i, j) > 0\}$  is an indicator for whether the match between  $i$  and  $j$  is formed after actual or placebo displacement, and  $e_{jt}$  is the residual error term. The coefficients

<sup>26</sup>Specifically, we use this specification to estimate the data analog of  $\gamma_{\Delta q_f | R} = \mathbb{E}[q_f(\tau) - q_f(t_0) | D_R = 1, D_B = 1, D = 1] - \mathbb{E}[q_f(\tau) - q_f(t_0) | D_R = 1, D_B = 1, D = 0]$ , where  $\phi_{t_M > 0}$  is the coefficient of interest that identifies  $\gamma_{\Delta q_f | R}$ .

<sup>27</sup>We refer to two individuals,  $i$  and  $j$ , as “matched” if they are married or in a cohabiting relationship. We refer to the first period in which  $i$  and  $j$  are observed being married or cohabiting as “the period in which the match between  $i$  and  $j$  was formed”.

<sup>28</sup>Specifically, the mapping  $i(j)$  assigns to each individual  $j$  the individual  $i$  with whom  $j$  was matched during the time window  $t = -5, \dots, 10$ . To ensure that this mapping is many-to-one, we exclude 65 individuals  $j$  (0.05% of our sample) who are matched with different individuals in our treatment or control group at different points in time. The mapping is many-to-one (rather than one-to-one) as our sample does include all partners  $j$  that  $i$  is matched with at some point during the time window  $t = -5, \dots, 10$ .

of interest,  $\phi_{t_M > 0}$ , capture the effect of job displacement on which types of partners individuals match with in the treatment group compared with the control group. To estimate  $\phi_{t_M > 0}$ , we leverage changes in matching patterns around actual displacement in the treatment group and compare them to changes around placebo displacement in the control group.

## 4 Empirical Results

This section presents our empirical results. We establish four main empirical findings: (i) Job displacement increases the risk of relationship dissolution; (ii) Job displacement especially increases the risk of relationship dissolution for men matched with low-earning women; (iii) Displaced men have a higher risk of remaining single post breakup than nondisplaced men; (iv) Job displacement leads men to transition to higher earning women post-breakup, compared with non-displaced men.

Section 4.1 documents the long-run effect of job displacement on employment and earnings. Sections 4.2-4.4 report our main empirical findings. In Section 4.5, we support our results with several robustness checks, ruling out that our empirical findings are driven by men who move to municipalities with favorable marriage market conditions. We further provide back-of-the-envelope calculations that suggest that establishment closures are unlikely to trigger substantial marriage or labor market equilibrium effects.

### 4.1 Labor Income, Employment, Hourly Wages, and Work Hours

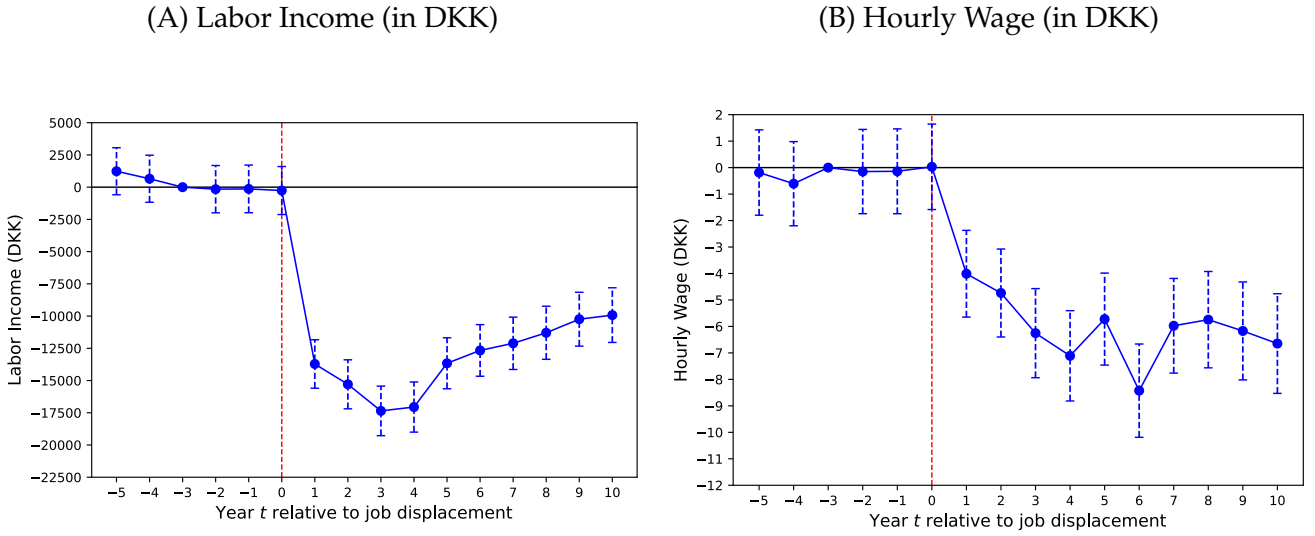
First, we document the effects of job displacement on employment and earnings. After job displacement, men's labor incomes drop sharply and persistently remain low. This pattern is driven predominantly by men taking on jobs at lower hourly wages post-displacement and, to a lesser extent, by reductions in employment and work hours.

Figure 1A shows that job displacement is a persistent negative shock to labor earnings. The figure displays estimates of  $\phi_\tau$ , measuring the differential evolution of labor income in treatment and control group after actual or placebo displacement. The trend prior to displacement is flat, and there is a pronounced drop in earnings post-displacement, reaching  $-17,354$  DKK in  $t = 3$ , a 5% drop compared with men's average earnings in  $t = -3$ . Post-displacement, labor income remains depressed for at least 10 years. The average effect over our post-displacement event-time window amounts to  $-13,332$  DKK,  $-4\%$  of men's average earnings in  $t = -3$ .<sup>29</sup> Figures 1B and C.1A and B show that the long-run effect on labor income is driven by men transitioning to jobs that pay lower hourly wages, and, to a lesser extent, by reductions in work hours and employment.

---

<sup>29</sup>The average effect over our post-displacement event-time window is computed as  $\frac{1}{10} \sum_{\tau=1}^{10} \phi_\tau$ .

Figure 1: Labor Market Effects of Job Displacement



*Notes:* The figure shows the impact of job displacement on annual labor income (including zeros for nonemployed individuals, Panel A), and hourly wages (conditional on employment, Panel B) measured in DKK (CPI 2004). The dashed vertical lines are 95% confidence intervals. The estimates correspond to estimates of  $\phi_\tau$  from Equation (7). All estimates are based on a sample of men who were displaced as part of an establishment closure between 1980 and 2007, and the same number of control individuals selected by coarsened exact matching. The specific sample selection criteria and matched sampling algorithm are described in Subsection 3.3.

## 4.2 Relationship Status

This subsection shows that job displacement increases the risk of relationship dissolution and that displaced men are more likely to remain single after a breakup than nondisplaced men are. Figures 2A-C show the dynamic effects of job displacement on the probability of being separated (Figure 2A), being single (Figure 2B) or being matched with a new partner (Figure 2C).

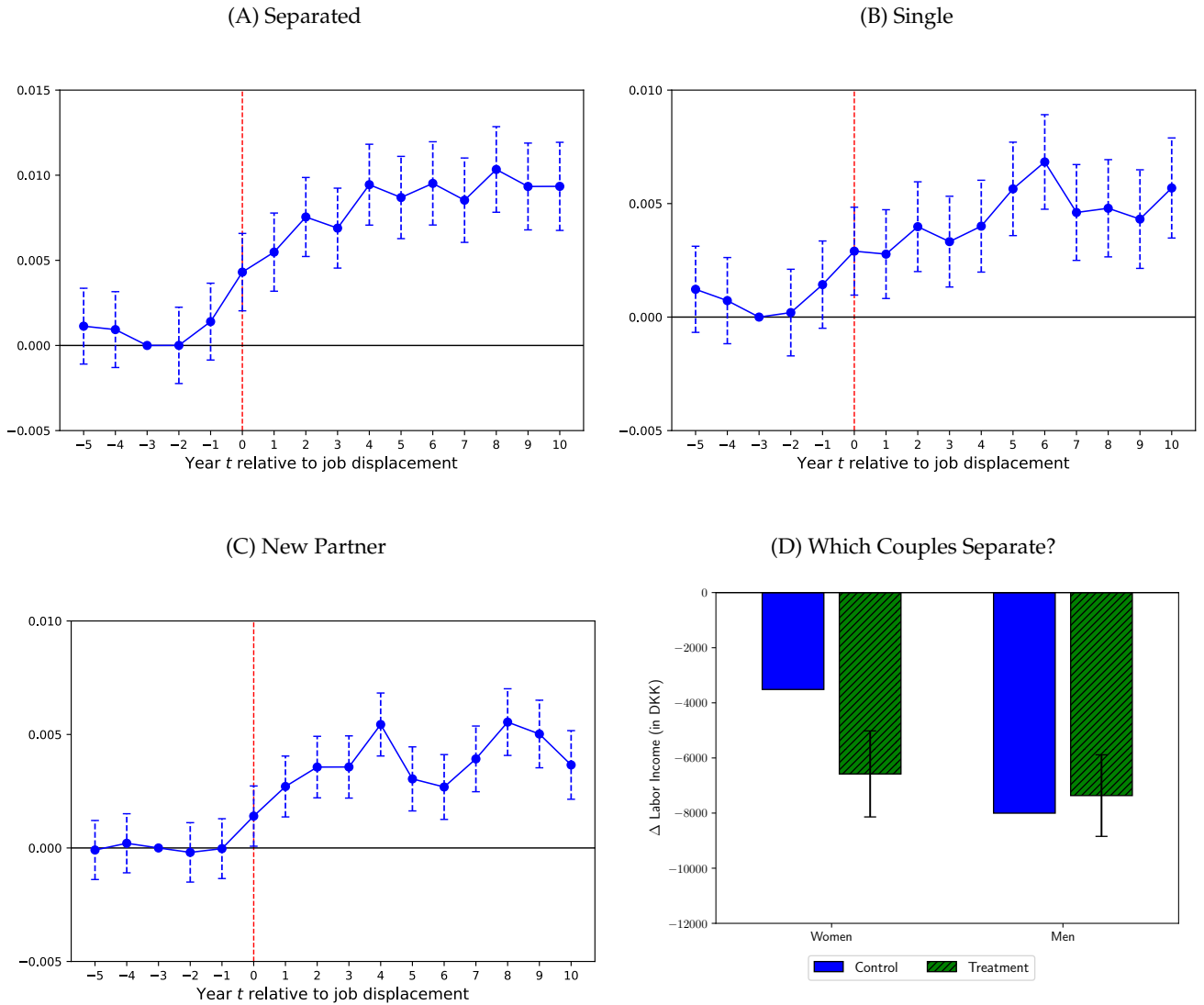
Figure 2A measures the effect on separations, using an indicator for not living with the same partner as in  $t = -3$  as the outcome variable<sup>30</sup> and documents a statistically significant increase in separations after job displacement, building up to 0.01 in  $t = 10$ , a 6% increase compared to the separation rate in the control group between  $t = -3$  and  $t = 10$ , which is at 0.18.<sup>31</sup> Thus, job displacement leads to an increase in separations, in line with the model predictions (under PAM and NAM) derived in Section 2.

Figure 2B and C decompose the effect on separation into the effect on being single and being on matched with a new partner. We use indicators for not living with a partner (in panel B) and for living with a partner different from the one in  $t = -3$  (in panel C) as outcome variables. Each effect is statistically significant. By construction, the estimates sum to the effect on separations, showing that approximately two-thirds of the effect on separations is driven by men who are single post-breakup, and one third by men living with new partners.

<sup>30</sup>This includes not living together with any partner and living together with a new partner who is distinct from the partner in  $t = -3$ .

<sup>31</sup>Huttunen and Kellokumpu (2016) and Eliason (2012) report comparable findings for Finland and Sweden, respectively.

Figure 2: Impact of Job Displacement on Relationship Status, and Which Couples Break Up



*Notes:* Panel A - C show the impact of job displacement on different measures of relationship status. Panel A shows the impact of job displacement on the probability of being separated from the pre-displacement partner. Panel B shows the impact of job displacement on the probability of being single (i.e., unmarried and not cohabiting). Panel C shows the impact of job displacement on the probability of being matched (married or cohabiting) with a new partner who is distinct from the pre-displacement partner. The values in Panel A-D correspond to coefficient estimates of  $\phi_\tau$  in Equation (7). The dashed vertical lines are 95% confidence intervals. Panel D shows the effect of job displacement on the composition of women and men (in terms of their labor income) who experience a breakup. Each plotted bar shows average pre-displacement labor income, in  $t \in \{-5, \dots, -3\}$ , of men and women who experience a breakup after the male partner's actual or placebo displacement, i.e., between  $t = 0$  and  $t = 10$ . All values are normalized by the respective sample average. The underlying sample for all panels is our sample of men who were displaced as part of an establishment closure between 1980-2007, and the same number of control individuals selected by coarsened exact matching. The specific sample selection criteria and matched sampling algorithm are described in Subsection 3.3.

Additionally, we compare the probability of staying single post-breakup between actual and placebo displaced men. Table B.2 reports differences between actual and placebo displaced men in (i) the probability of being matched with a partner in  $t + 1$  conditional on having been single in  $t$ , and (ii) the probability of being matched with a partner at any point in time  $t = 1, \dots, 10$  after having been single in at least one

period,  $t > -3$ . Displaced men are statistically significantly less likely to transition out of being single by either measure. Note that these estimates include both a treatment effect on a given man's chances of finding a partner and a selection effect by which job displacement potentially causes breakups among men with above- or below-average chances of finding a new partner.

### 4.3 Which Couples Separate?

Next, we demonstrate that men who experience a breakup after being displaced tend to be matched with low-earning women. We consider couples' pre-displacement earnings in  $t \in \{-5, \dots, -3\}$  to circumvent the direct effect of displacement on men's incomes and draw comparisons between couples in the treatment and control group who break up within 10 years after actual or placebo displacement.

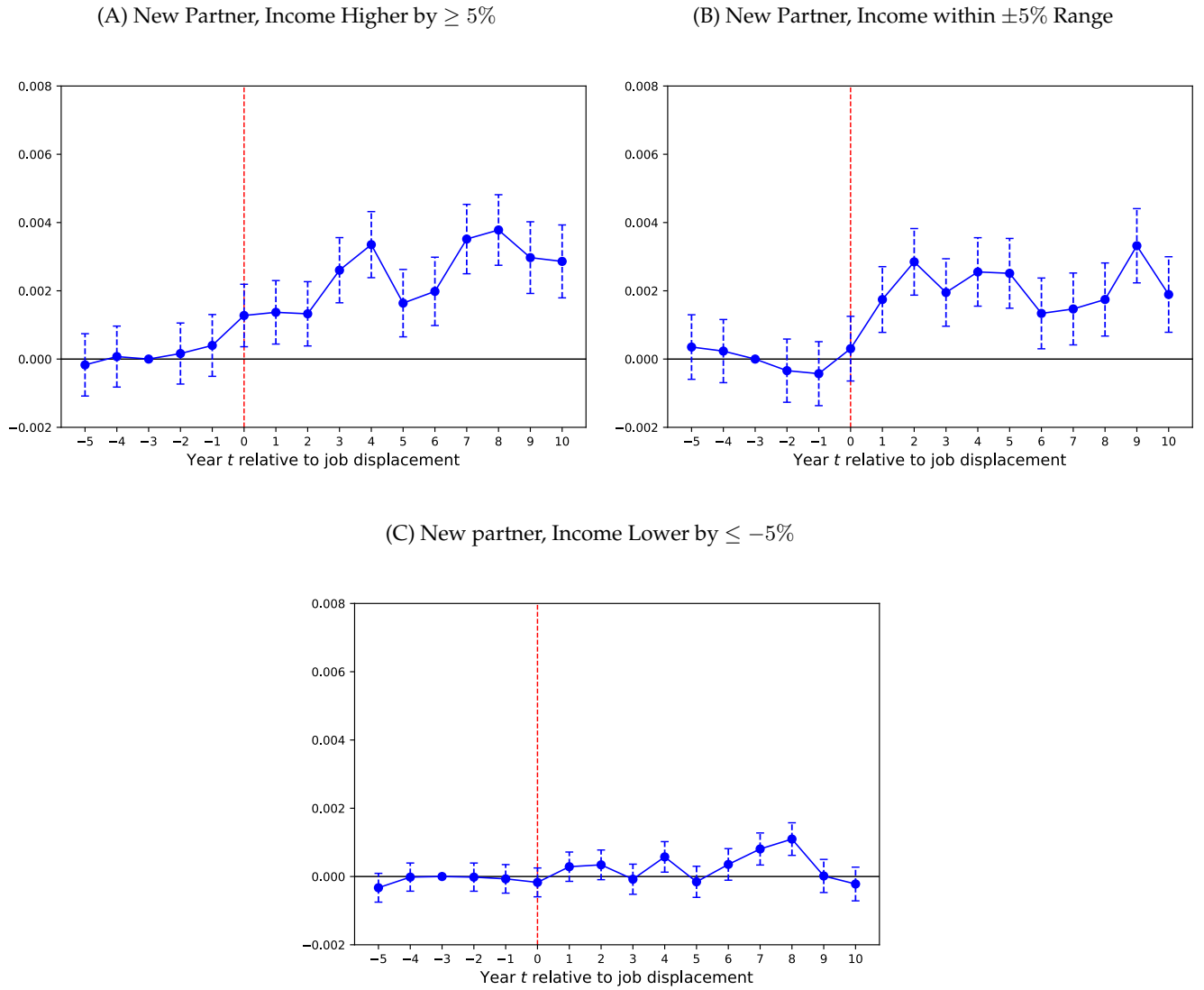
Figure 2D shows the average pre-displacement labor income, in  $t \in \{-5, \dots, -3\}$ , of men and women who experience a breakup between  $t = 0$  and  $t = 10$  normalized by the respective sample average.<sup>32</sup> Our results show that people who experience a breakup are generally below-average earning. This is true for both women and men in the treatment and control group. More importantly, women in dissolving couples that were matched with an actually displaced man have lower earnings than women in dissolving couples who were matched with a placebo displaced man. The difference is statistically significant at -3063 DKK, 23% of the average income loss of a displaced man. The difference between the earnings of men in dissolving couples in the treatment group and those in the control group is modestly positive but statistically insignificant. These results demonstrate that job displacement especially increases the risk of relationship dissolution for men matched with low-earning women.

We repeat the same analysis steps for outcomes other than labor income to gauge the extent to which dissolving couples in the treatment and control group differ in other dimensions. Figure C.3 shows that there are no statistically significant differences between treatment and control group in men and women's age, or couples' number of children. Women and men in dissolving couples in the treatment group have statistically significantly fewer years of schooling relative to the control group, but the differences are small in magnitude (less than 0.05 years).

To invoke implication 5.-a or 5.-b of Proposition 1 (showing which types of women men in the treatment and control group separate from on average), we additionally need to confirm whether our data are consistent with the condition  $F(q_m|D_B = 1, D = 1) \leq F(q_m|D_B = 1, D = 0)$  or  $F(q_m|D_B = 1, D = 1) \geq F(q_m|D_B = 1, D = 0)$ . To empirically assess whether either condition is satisfied, Figure C.2 plots the empirical cdf of labor income in  $t \in \{-5, \dots, -3\}$  for actual and placebo displaced men who experience breakup between  $t = 0$  and  $t = 10$ . The figure shows that the empirical cdfs for these two groups are strikingly similar. A Kolmogorov-Smirnov test fails to reject the hypothesis of equality between the two distributions (p-value: 0.539). Empirically, the conditions of Proposition 1, 5.-a and 5.-b do not appear to be violated.

<sup>32</sup>Note that displacement refers to the actual or placebo displacement of the male partner in the considered couples. Women

Figure 3: Impact of Job Displacement on New Partners' Income



*Notes:* The displayed results show the effect of job displacement on the female type a man rematches with after a breakup, where the type is measured in terms of annual labor income. Panel A shows the impact of job displacement on the probability of matching with a new partner (who is distinct from the pre-displacement partner) who outearns the pre-displacement partner by at least 5%. Panel B shows the impact of job displacement on the probability of matching with a new partner who earns 95% or less of the pre-displacement partner's income. Panel C shows the impact of job displacement on the probability of matching with a new partner who earns within a  $\pm 5\%$  range of the pre-displacement partner's income. The estimates correspond to estimates of  $\phi_\tau$  in Equation (7). The dashed vertical lines are 95% confidence intervals. All estimates are based on a sample of men who experienced an establishment closure between 1980 and 2007, and the same number of control individuals selected by exact matching. The sample selection criteria and matching algorithm are described in subsection 3.3.

#### 4.4 Which Types of Partners do Men Rematch with?

We now turn to analyzing how job displacement affects which types of partners men rematch with after breakup. Our findings show that displaced men are more likely to transition from low-earning to higher-earning partners than men in the control group. We do not find substantial effects of job displacement on matching patterns in terms of other partner characteristics, including age and education.

First, we consider the propensity of transitioning to a higher earning, similarly earning, or lower-earning

---

are assigned to treatment or control group according to their male partner's treatment status.

new partner compared with the pre-displacement partner in the treatment versus the control group. To this end, we estimate Equation (7) using three types of indicators as outcome variables:

$$\begin{aligned} Y_{it}^+ &= \mathbf{1} \{Y_{it} \geq (1 + \rho)Y_{it}^{\text{pre}}\} \cdot D_{Rt}, \\ Y_{it}^0 &= \mathbf{1} \{(1 - \rho)Y_{it}^{\text{pre}} < Y_{it} < (1 + \rho)Y_{it}^{\text{pre}}\} \cdot D_{Rt}, \\ Y_{it}^- &= \mathbf{1} \{Y_{it} \leq (1 - \rho)Y_{it}^{\text{pre}}\} \cdot D_{Rt}, \end{aligned}$$

where  $Y_{it}$  denotes the earnings of the partner with whom individual  $i$  is matched in period  $t$ .  $Y_{it}^{\text{pre}}$  denotes the earnings of the partner with whom individual  $i$  was matched pre-displacement, in period  $t = -3$ .  $\rho$  is a threshold value that we choose, and  $D_{Rt}$  is an indicator for living with a partner different from the one in  $t = -3$ . According to this definition,  $Y_{it}^+$  indicates that  $i$  transitioned to a new partner who outearns his pre-displacement partner by at least  $\rho \cdot 100\%$ ,  $Y_{it}^0$  indicates that  $i$  transitioned to a new partner who earns within a  $\pm \rho \cdot 100\%$  range of his pre-displacement partner, and  $Y_{it}^-$  indicates that  $i$  transitioned to a new partner who earns  $(1 - \rho) \cdot 100\%$  or less than his pre-displacement partner. For our main analysis, we fix  $\rho = 0.05$ , and use annual labor income as measure of earnings.<sup>33</sup>

Figures 3A-C show that job displacement increases the likelihood of transitioning to either higher or similarly earning partners, but not the likelihood of transitioning to lower-earning partners. The figure displays estimates of  $\phi_\tau$  in Equation (7), using  $Y_{it}^+$ ,  $Y_{it}^0$ , and  $Y_{it}^-$  as outcome variables. The effects on transitions to higher and similarly earning partners are statistically significant at 0.003 and 0.002 in  $t = 10$ , a 8.5% and 5.3% increase relative to the control group. These results show that displaced men are more likely to transition from low-earning to higher-earning partners compared than men in the control group.

We additionally estimate specification (8) to assess the average gain in partner income associated with transitioning to a new partner post displacement. Specifically, we use specification (8) to estimate<sup>34</sup>

$$\gamma_{\Delta q_f|R} = \mathbb{E}[q_f(\tau) - q_f(t_0)|D_R = 1, D_B = 1, D = 1] - \mathbb{E}[q_f(\tau) - q_f(t_0)|D_R = 1, D_B = 1, D = 0],$$

and use the estimate to assess whether our empirical findings can be reconciled with our model predictions derived in Section 2. Table 1 reports estimates of  $\phi_{t_M > 0}$  from Equation (8), using annual labor income, hourly wages, and work hours as outcome variables. The coefficient estimate in Column (1) shows that, compared with the control group, displaced men experience a statistically significant increase in partner earnings of 3269 DKK when transitioning to a new partner post displacement. Scaling this estimate by the average income loss from job displacement, which we estimate at  $\Delta q_m = -13,332$  DKK (see Section 4.1), yields

$$\frac{\gamma_{\Delta q_f|R}}{\Delta q_m} = -0.25,$$

<sup>33</sup>Varying the value of  $\rho$  or using hourly wages as measure of earnings delivers qualitatively similar results. Figures C.4 and C.5 report results for  $\rho = 0.1$  and for using hourly wages as the measure of earnings.

<sup>34</sup>Note that  $\phi_{t_M > 0}$  is the data analog of  $\gamma_{\Delta q_f|R}$ .



implying that among the subgroup of men who experience a breakup and rematch with a new partner, a 1 unit loss in own income is associated with matching with a 0.25 unit higher earning partner. Note that this estimate includes both a treatment effect on a given man's chances of matching with particular female types and a selection effect by which job displacement potentially causes men to break up and rematch who have above- or below-average chances of finding a high-earning new partner.

Columns (2) and (3) of Table 1 report separate estimates for hourly wages and work hours as outcome variables, showing that the estimate for labor income is driven by differences in partners' hourly wages rather than differences in their labor supply.

Table 1: Impact of Job Displacement on New Partners' Income, Wage, and Work Hours

	Labor Income	Wage	Work Hours
Treated $\times$ post-displacement, $\phi_{t_M > 0}$	3269.01** (1614.72)	2.58* (1.38)	-0.12 (0.13)
No. of observations	108,982	79,796	53,702

*Notes:* The table shows the effect of job displacement on the types of partners men transition to in terms of their labor income, hourly wage (conditional on employment), and work hours (including zeros for non-employed individuals). The table reports coefficient estimates of  $\phi_{t_M > 0}$  from Equation (8). Standard errors are reported in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

To gauge the extent to which job displacement affects matching patterns in terms of other partner characteristics, we additionally estimate specification (8) using age, education (years of schooling), and number of children from previous relationships as outcome variables. Table 2 shows that job displacement induces men to transition to younger partners with more children. The coefficient estimates are statistically significant but very modest in magnitude. For partner age, the coefficient estimate is -0.27 years, while for the number of children it is 0.04. The effect on partner education is small and statistically insignificant at -0.04 years of schooling.

Table 2: Impact of Job Displacement on New Partners' Age, Education, and No. of Children

	Age	Education	No. of children
Treated $\times$ post-displacement, $\phi_{t_M > 0}$	-0.27*** (0.09)	-0.04 (0.03)	0.04*** (0.01)
No. of observations	108,982	108,982	108,982

*Notes:* The table shows the effect of job displacement on the types of partners men transition to in terms of their age, education (measured in years of schooling) and number of children. The table reports coefficient estimates of  $\phi_{t_M > 0}$  from Equation (8). Standard errors are reported in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .



## 4.5 Robustness

We rule out several alternative explanations for our empirical findings. First, we rule out that our findings are driven by men who move to municipalities populated by high-earning single women. Second, we exclude that displaced men move to municipalities in which single men are scarce relative to single women, and therefore face less competition in the marriage market. Third, we provide back-of-the-envelope calculations that suggest it is unlikely that establishment closures trigger substantial marriage or labor market equilibrium effects.

**Moves Across Municipalities and Local Marriage Market Conditions** We consider the role of moves to different municipalities that are triggered by job displacement. Figure C.6A shows how displacement affects the propensity to move by estimating Equation (7), using an indicator variable for whether the individual lives in a different municipality compared to his residence measured in  $t = -3$  (i.e., before actual or placebo displacement) as the outcome variable. The figure shows that the impact of displacement on the likelihood of having moved to a different municipality is positive and statistically significant at 1.16 percentage points 10 years after displacement. To check whether these are moves to municipalities with favorable marriage market conditions, we consider two robustness checks. First, we examine whether job displacement induces moves to municipalities populated by high-earning single women. To do so, we estimate Equation (7) using the average earnings of single women in the municipality the individual resides in as the outcome variable.

Second, we explore whether job displacement triggers moves to municipalities in which single men are scarce relative to single women, which would mean they face low competition in the marriage market.<sup>35</sup> We estimate Equation (7) using the sex-ratio in the municipality the individual resides in as the outcome variable. Figure C.6B and C show that job displacement has no statistically significant effect on either of these outcomes.

**Labor Market and Marriage Market Equilibrium Effects of Establishment Closures** We gauge whether it is likely that establishment closures exert notable labor market or marriage market equilibrium effects by performing a back of the envelope calculation. The workforce of the average closing establishment in our sample is 55 workers, 0.6% of the average local labor force in municipalities that contain a closing establishment. The rate at which displaced workers separate from their partners within the 10 years following establishment closure is 0.2 in our sample. The average inflow of singles into a the marriage market over 10 years due to an establishment closure is thus approximately  $0.2 \times 55 = 11$ . This amounts to an influx of 1.5% relative to the average local population of singles who are 28-48 years old in municipalities that contain a closing establishment.

---

<sup>35</sup>We define the sex ratio on a local marriage market as the number of single women divided by the number of single men in a municipality.

## 4.6 Confronting Theory and Data

We are now ready to confront theory and data, by comparing the predictions we have derived within our conceptual framework with our empirical findings. Table 3 summarizes our empirical results vis-à-vis the model predictions, which we derived in Proposition 1. Our empirical findings are largely consistent with our conceptual framework under NAM. This is true for all our empirical evidence from job displacement. Under PAM, in contrast, our conceptual framework predicts that men transition away from high-earning toward lower-earning women ( $\gamma_{q_f|B} \geq 0$  and  $\gamma_{\Delta q_f|R} \leq 0$ ), which is rejected by our data. At the same time, the cross-sectional correlation between matched partners' incomes in our data is positive (0.15), which is consistent with PAM and inconsistent with NAM (see Equations (5) and (6)).

In summary, our empirical evidence from job displacements is consistent with NAM but not with PAM. By contrast, the positive cross-sectional correlation between matched partners' incomes is consistent with PAM, but not with NAM. Under one-dimensional matching, our conceptual framework cannot simultaneously account for our evidence from job displacements and the positive correlation between matched partners' incomes, under neither NAM nor PAM.

Quantitatively, our conceptual framework predicts that under PAM,  $\gamma_{\Delta q_f|R}$  is not only weakly negative, but also bounded away from zero by  $\bar{\gamma}_{\Delta q_f|R}$  (see Proposition 1). To provide a simple check of this relationship, we approximate  $\frac{\partial \mathbb{E}[q_f|q_m]}{\partial q_m}$  by the slope coefficient,  $\beta$ , obtained by regressing wives' income on husbands' income and a constant.<sup>36</sup> Under this approximation, relationship 4.-a of Proposition 1 simplifies to  $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m} \geq \beta$ .<sup>37</sup> Figure 4 shows our estimate of  $\beta$  at 0.17, whereas we estimated that  $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m} = -0.25$  (see Section 4.4), showing that our estimates are far from satisfying the quantitative restriction,  $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m} \geq \beta$ , which is implied by our conceptual framework under PAM.

Table 3: Confronting Theory and Data

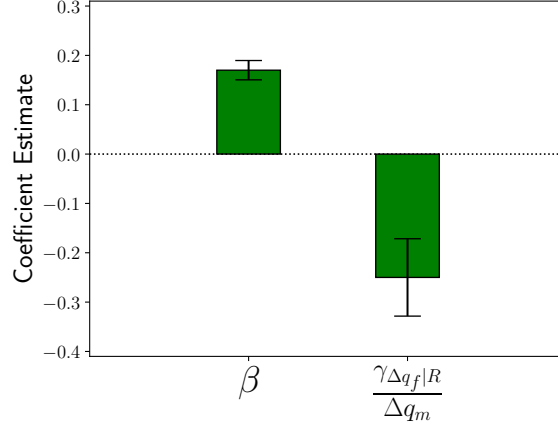
Impact of job displacement on		Data	NAM	PAM
Breakup risk	$\gamma_B$	$\geq 0$	$\geq 0$	$\geq 0$
Risk of remaining single post breakup	$\gamma_{R=0 B}$	$\geq 0$	unrestricted	unrestricted
Which female types experience a break up	$\gamma_{q_f B}$	$\leq 0$	$\leq 0$	$\geq 0$
Female types men rematch with after a breakup	$\gamma_{\Delta q_f R}$	$\geq 0$	$\geq 0$	$\leq 0$
Cross-sectional income correlation	$\text{Corr}(\text{income}_f, \text{income}_m)$	$\geq 0$	$\leq 0$	$\geq 0$

*Notes:* The table summarizes the predictions implied by our conceptual framework and NAM and PAM that we derive in Proposition 1 in Section 2, and our empirical findings reported in Section 4.

<sup>36</sup>As is well known,  $\beta = \frac{\text{Cov}(q_f, q_m)}{\text{Var}(q_m)}$  provides the best linear predictor of  $\frac{\partial \mathbb{E}[q_f|q_m]}{\partial q_m}$  in terms of minimizing the mean squared prediction error between  $\mathbb{E}[q_f|q_m]$  and  $\alpha + \beta q_m$  (see, e.g., [Goldberger 1991](#)).

<sup>37</sup>To see this, note that using  $\frac{\partial \mathbb{E}[q_f|q_m]}{\partial q_m} \approx \beta$ , it follows that  $\bar{\gamma}_{\Delta q_f|R} \approx -d\beta = \Delta q_m \beta$ . Dividing  $\gamma_{\Delta q_f|R} \leq \Delta q_m \beta$  by  $\Delta q_m \leq 0$  yields  $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m} \geq \beta$ .

Figure 4: Correlational Evidence vs. Evidence from Establishment Closures



*Notes:* The figure displays the regression coefficient of regressing wife's on husband's income,  $\beta$ , alongside our estimate of the change in partner income associated with transitioning to a new partner after job displacement,  $\frac{\gamma_{\Delta q_f | R}}{\Delta q_m}$ . The capped error bars are 95% confidence intervals.

## 5 Reconciling Theory and Data: Multidimensional Matching

This section discusses a possible theoretical explanation for our empirical findings. In Section 4.6, we argued that our one-dimensional conceptual framework under PAM or NAM cannot simultaneously account for: first, our evidence that men transition away from low-earning to higher-earning partners after job loss; second, the positive correlation between matched partners' incomes. In this section, we argue that under multidimensional matching our conceptual framework is capable of capturing both of these empirical facts simultaneously.

We consider the framework described in Section 2.1 in the multidimensional case,  $K > 1$ . Our definitions of flow utilities, value functions, and marital surplus from Subsection 2.1 carry over to the case where  $q_f$  and  $q_m$  are  $K$ -dimensional vectors. In the following subsections, we define multidimensional notions of PAM and NAM (dimension by dimension, similar to [Lindenlaub and Postel-Vinay 2023](#)). We then derive predictions regarding the effects of job displacement on marriage market matching in the  $K$ -dimensional version of our framework and propose conditions under which the multidimensional framework is consistent with both, our evidence from job displacement and the positive correlation between spouses' incomes.

### 5.1 Multidimensional Sorting

We extend the one-dimensional definitions of PAM and NAM given in Subsection 2.4 to the multidimensional case where  $q_f$  and  $q_m$  are  $K$ -dimensional vectors. Consider the general matching environment described in Section 2 which is summarized by (2)–(4). Denote by  $\mathcal{M}(q_m) = \{q_f \in Q_f : S(q_f, q_m) \geq 0\}$  the multidimensional matching set of a model agent of type  $q_m$ . It will occasionally be useful to denote  $q_f$  by  $(q_{fi}, q_f^{-i})$ , where  $q_{fi}$  denotes the  $i$ -th component and  $q_f^{-i}$  denotes all but the  $i$ -th components of vector  $q_f$ . We define positive and negative assortative mating in dimension  $i$ , write PAM(i) and NAM(i), as follows:

**Definition 2.** Consider  $q'_{fi} < q''_{fi}$ ,  $q'_{mi} < q''_{mi}$ .

There is PAM(i) if for all  $q_f^{-i}, q_m^{-i}$ :  $(q'_{fi}, q_f^{-i}) \in \mathcal{M}(q'_{mi}, q_m^{-i})$  and  $(q'_{fi}, q_f^{-i}) \in \mathcal{M}(q''_{mi}, q_m^{-i})$

$\Rightarrow (q'_{fi}, q_f^{-i}) \in \mathcal{M}(q'_{mi}, q_m^{-i})$  and  $(q''_{fi}, q_f^{-i}) \in \mathcal{M}(q''_{mi}, q_m^{-i})$ .

There is NAM(i) if for all  $q_f^{-i}, q_m^{-i}$ :  $(q'_{fi}, q_f^{-i}) \in \mathcal{M}(q'_{mi}, q_m^{-i})$  and  $(q''_{fi}, q_f^{-i}) \in \mathcal{M}(q''_{mi}, q_m^{-i})$

$\Rightarrow (q''_{fi}, q_f^{-i}) \in \mathcal{M}(q'_{mi}, q_m^{-i})$  and  $(q'_{fi}, q_f^{-i}) \in \mathcal{M}(q''_{mi}, q_m^{-i})$ .

Next, we show that under either PAM(i) or NAM(i) there is a (weakly) monotonic relationship between matching sets and the  $i$ -th component of agent type (generalizing the corresponding one-dimensional property derived by [Shimer and Smith 2000](#)). To do so, we invoke the following additional assumption, requiring that sets of the form  $\{q_{fi} : (q_{fi}, q_f^{-i}) \in \mathcal{M}(q_m)\}$  are nonempty.

**A-1.** For any given  $q_m$  and  $q_f^{-i}$  there exists a  $q_{fi}$ , such that  $(q_{fi}, q_f^{-i}) \in \mathcal{M}(q_m)$ . For any given  $q_f$  and  $q_m^{-i}$  there exists a  $q_{mi}$ , such that  $(q_{mi}, q_m^{-i}) \in \mathcal{M}(q_f)$ .

Intuitively, **A-1** is satisfied if for a man with characteristics  $q_m$  and a woman with characteristics  $q_f^{-i}$  there exists a value of characteristic  $q_{fi}$  sufficiently favorable such that  $q_m$  and  $(q_{fi}, q_f^{-i})$  would agree to match upon meeting. Leveraging **A-1**, we establish the following relationship between sorting and multidimensional matching sets.

**Lemma 1.** Under assumption **A-1**, and given either PAM(i) or NAM(i), multidimensional matching sets,  $\mathcal{M}(q_m)$ , are characterized by one-dimensional sets

$$\{q_{fi} : (q_{fi}, q_f^{-i}) \in \mathcal{M}(q_m)\} = [a_i(q_{mi}, q_m^{-i}, q_f^{-i}), b_i(q_{mi}, q_m^{-i}, q_f^{-i})],$$

where

$$q_f \in \mathcal{M}(q_m) \Leftrightarrow q_{fi} \in [a_i(q_{mi}, q_m^{-i}, q_f^{-i}), b_i(q_{mi}, q_m^{-i}, q_f^{-i})]$$

and  $a_i, b_i$  are

- (i) weakly increasing in  $q_{mi}$  under PAM(i),
- (ii) weakly decreasing in  $q_{mi}$  under NAM(i).

Intuitively, Lemma 1 states that given male and female characteristics  $q_m^{-i}$  and  $q_f^{-i}$ , the remaining  $i$ -th dimension of the matching set  $\mathcal{M}(q_m)$  is an interval with bounds that are weakly increasing in  $q_{mi}$  under PAM(i) and weakly decreasing in  $q_{mi}$  under NAM(i).

## 5.2 Job Loss and Multidimensional Matching

Next, we use the described multidimensional framework to derive predictions regarding the effects of job displacement that we identified in our empirical analysis. We interpret job displacement as a permanent

change in the  $i$ -th dimension of a displaced agent's type. More specifically, a man of type  $q_m$  who is displaced from his job suffers a permanent unexpected reduction in  $q_{mi}$  to  $q_{mi} - d$ , where  $d > 0$ . Similar to the one-dimensional case, we assume that  $q_{mi}$  maps into labor income by an increasing one-to-one mapping.<sup>38</sup> To derive predictions regarding the effects of job displacement, we consider the same setup as described in Section 2.5 (a treatment group displaced in  $t_0$ , and a control group that is not displaced in  $[t_0, \tau]$ ). The definitions of the effects of job displacement  $\gamma_B$  and  $\gamma_{R=0|B}$  carry over from Section 2.5. We further define

$$\gamma_{q_{mi}|B} = \mathbb{E}[q_{mi}(t_0)|D_B = 1, D = 1] - \mathbb{E}[q_{mi}(t_0)|D_B = 1, D = 0],$$

$$\gamma_{q_{fi}|B} = \mathbb{E}[q_{fi}(t_0)|D_B = 1, D = 1] - \mathbb{E}[q_{fi}(t_0)|D_B = 1, D = 0],$$

$$\gamma_{\Delta q_{fi}|R} = \mathbb{E}[q_{fi}(\tau) - q_{fi}(t_0)|D_R = 1, D_B = 1, D = 1] - \mathbb{E}[q_{fi}(\tau) - q_{fi}(t_0)|D_R = 1, D_B = 1, D = 0]$$

analogously to the corresponding objects from Section 2.5. We show that the following relationships between marriage market sorting and the effects of job displacement hold under multidimensional matching, analogous to the one-dimensional case.

**Proposition 2.** *Consider the described matching environment in steady-state equilibrium in the multidimensional case,  $K > 1$  and suppose A-1 holds.*

*Under either PAM(i) or NAM(i):*

1. *Job displacement increases the separation risk:  $\gamma_B \geq 0$ .*
2. *Job displacement may increase or decrease the probability of staying single:*

*$\gamma_{R=0|B}$  may be positive or negative.*

*Under PAM(i):*

- 3.-a *Job displacement leads men to rematch with women of lower type:  $\gamma_{\Delta q_{fi}|R} \leq 0$ .*
- 4.-a *The association between job displacement and partner type is bounded above:  $\gamma_{\Delta q_{fi}|R} \leq \bar{\gamma}_{\Delta q_{fi}|R}$ .*

*The upper bound is given by*

$$\bar{\gamma}_{\Delta q_{fi}|R} = - \int \int \int_0^d \frac{\partial \mathbb{E}[q_{fi}|q_{mi}, q_m^{-i}, q_f^{-i}]}{\partial q_{mi}} \bigg|_{q_{mi}=q-x} dx dG_f^{-i}(q_f^{-i}) dF(q|D_R = 1, D_B = 1, D = 1) \leq 0.$$

- 5.-a *If  $F(q_{mi}|D_B = 1, D = 1) \leq F(q_{mi}|D_B = 1, D = 0)$  holds additionally, then, on average, women from whom displaced men separate are of higher type than women from whom nondisplaced men separate:  $\gamma_{q_{fi}|B} \geq 0$ .*

<sup>38</sup>Note that other observable attributes than labor income may map one-to-one into  $q_{mi}$  and be affected by job displacement as well. The distinguishing feature of the multidimensional case is that other dimensions  $j \neq i$  of  $q_m$  exist that are not shocked by job displacement. The idea is that while some agent characteristics, such as earnings potential or health are permanently reduced (see, e.g., Eliason and Storrie 2006; Browning, Moller Dano, and Heinesen 2006; Sullivan and von Wachter 2009), other characteristics such as an agent's age or height remain unchanged.

Under NAM(i):

3.-b Job displacement leads men to rematch with women of higher type:  $\gamma_{\Delta q_{fi}|R} \geq 0$ .

4.-b The association between job displacement and partner type is bounded below:  $\gamma_{\Delta q_{fi}|R} \geq \underline{\gamma}_{\Delta q_{fi}|R}$ .

The lower bound is given by

$$\underline{\gamma}_{\Delta q_{fi}|R} = - \int \int \int_0^d \frac{\partial \mathbb{E} [q_{fi} | q_{mi}, q_m^{-i}, q_f^{-i}]}{\partial q_{mi}} \bigg|_{q_{mi}=q-x} dx dG_f^{-i}(q_f^{-i}) dF(q | D_R = 1, D_B = 1, D = 1) \geq 0.$$

5.-b If  $F(q_{mi} | D_B = 1, D = 1) \geq F(q_{mi} | D_B = 1, D = 0)$  holds additionally, then, on average, women from whom displaced men separate are of lower type than women from whom non-displaced men separate:  $\gamma_{q_{fi}|B} \leq 0$ .

Proposition 2 establishes that the claims established in Proposition 1 carry over to the multidimensional case up to minor modifications.

### 5.3 Cross-Sectional Correlations and Multidimensional Matching

We show that under multidimensional matching our conceptual framework can capture our empirical evidence from job displacements as well as the positive correlation between matched partners' incomes. Intuitively, in the multidimensional framework we can have a negative relationship between  $q_{fi}$  and  $q_{mi}$ , ceteris paribus, keeping all other dimensions fixed, whereas the positive cross-sectional correlation between  $q_{fi}$  and  $q_{mi}$  arises spuriously from sorting in other dimensions that happen to correlate with  $q_{fi}$  and  $q_{mi}$ .

Formally, we investigate under which conditions the conditional expectation  $\mathbb{E}[q_{fi} | q_{mi}]$  is weakly increasing (weakly decreasing) in  $q_{mi}$ , which implies a weakly positive (weakly negative) correlation between  $q_{fi}$  and  $q_{mi}$ . Specifically, we decompose the effect of increasing  $q_{mi}$  on  $\mathbb{E}[q_{fi} | q_{mi}]$  into a direct effect ( $DE$ ), which captures the impact of ceteris paribus increasing  $q_{mi}$  while holding  $q_m^{-i}$  fixed, and an indirect effect ( $IE$ ), which captures the association between  $q_{fi}$  and  $q_{mi}$  that arises from sorting on  $q_m^{-i}$  and  $q_f^{-i}$ . We then derive sufficient conditions that determine the signs of  $DE$  and  $IE$ . To this end, we invoke the following additional assumption on the orientation of matching sets.

**A-2.** For any given dimensions  $i$  and  $j$ , and any  $q'_{fi} < q''_{fi}$ ,  $q'_{fj} < q''_{fj}$ ,  $q_f^{-(i,j)}$ , and  $q_m$  it holds that:

$$\begin{aligned} & (q'_{fi}, q'_{fj}, q_f^{-(i,j)}) \in \mathcal{M}(q_m) \text{ and } (q''_{fi}, q''_{fj}, q_f^{-(i,j)}) \in \mathcal{M}(q_m) \\ \Rightarrow & (q'_{fi}, q''_{fj}, q_f^{-(i,j)}) \in \mathcal{M}(q_m) \text{ and } (q''_{fi}, q'_{fj}, q_f^{-(i,j)}) \in \mathcal{M}(q_m). \end{aligned}$$

Intuitively, A-2 is satisfied if there is a trade-off between  $q_{fi}$  and  $q_{fj}$ , in the sense that for a man of given type  $q_m$ , matches with partners who are high-type in one but low-type in the other dimension are more likely than matches with partners who are high-types or low-types in both dimension  $i$  and  $j$ .

For simplicity, Proposition 3 provides the result for the bidimensional special case,  $K = 2$ . The result for the general multidimensional case,  $K > 1$ , requires additional notation as well as additional assumptions on the joint distribution of  $q_m^{-i}$ , and is provided in Proposition 4 in Appendix A.<sup>39</sup>

**Proposition 3.** *Consider the described matching environment in the bidimensional case,  $K = 2$ , and suppose that A-1 and A-2 hold.*

*Consider the following decomposition for  $q''_{mi} \geq q'_{mi}$*

$$\begin{aligned} \mathbb{E}[q_{fi}|q''_{mi}] - \mathbb{E}[q_{fi}|q'_{mi}] &= \underbrace{\int \mathbb{E}[q_{fi}|q''_{mi}, q_{mj}] - \mathbb{E}[q_{fi}|q'_{mi}, q_{mj}] dG(q_{mj}|q''_{mi})}_{:= \text{DE (Direct effect)}} \\ &+ \underbrace{\int \mathbb{E}[q_{fi}|q'_{mi}, q_{mj}] dG(q_{mj}|q''_{mi}) - \int \mathbb{E}[q_{fi}|q'_{mi}, q_{mj}] dG(q_{mj}|q'_{mi})}_{:= \text{IE (Indirect effect)}}. \end{aligned}$$

*In a bidimensional steady-state matching equilibrium, the following implications hold:*

$$PAM(i) \Rightarrow DE \geq 0,$$

$$NAM(i) \Rightarrow DE \leq 0.$$

*Given PAM (i) or NAM (i), the following additional implications hold:*

$$PAM(j) \text{ and } G(q_{mj}|q_{mi}) \text{ is weakly decreasing in } q_{mi} \Rightarrow IE \geq 0,$$

$$NAM(j) \text{ and } G(q_{mj}|q_{mi}) \text{ is weakly decreasing in } q_{mi} \Rightarrow IE \leq 0,$$

$$PAM(j) \text{ and } G(q_{mj}|q_{mi}) \text{ is weakly increasing in } q_{mi} \Rightarrow IE \leq 0,$$

$$NAM(j) \text{ and } G(q_{mj}|q_{mi}) \text{ is weakly increasing in } q_{mi} \Rightarrow IE \geq 0.$$

Proposition 3 provides sufficient conditions for  $Corr(q_{fi}, q_{mi}) \geq 0$  and  $Corr(q_{fi}, q_{mi}) \leq 0$ .<sup>40</sup> Moreover, the proposition shows that even if sorting in dimension  $i$  is negative (i.e., under NAM (i)), a positive cross-sectional correlation between  $q_{fi}$  and  $q_{mi}$  is possible if  $IE$  is positive and larger than  $DE$  in magnitude.

## 5.4 Taking Stock

Together, Proposition 2 and Proposition 3 show that under multidimensional matching our conceptual framework can explain our empirical findings. Proposition 2 shows that the multidimensional framework predicts under NAM(i) that job displacement increases the risk of relationship dissolution ( $\gamma_B \geq 0$ ), and that men transition away from low-earning and toward higher-earning partners after job loss ( $\gamma_{q_f|B} \leq 0$  and  $\gamma_{\Delta q_f|R} \geq 0$ ), in line with our empirical findings presented in Section 4. Proposition 3 shows that at the same time a positive correlation between partners' incomes is possible, e.g., if it arises from sorting

<sup>39</sup>The condition that  $G(q_{mj}|q_{mi})$  is weakly increasing in  $q_{mi}$  is sometimes referred to as "positive regression dependence" (see, e.g., Lehmann 1966) and implies  $Corr(q_{mj}, q_{mi}) > 0$ .

<sup>40</sup>If  $DE \geq 0$  and  $IE \geq 0$  then  $\mathbb{E}[q_{fi}|q_{mi}]$  is weakly increasing in  $q_{mi}$ , which implies  $Corr(q_{fi}, q_{mi}) \geq 0$ . If  $DE \leq 0$  and  $IE \leq 0$  then  $\mathbb{E}[q_{fi}|q_{mi}]$  is weakly decreasing in  $q_{mi}$ , which implies  $Corr(q_{fi}, q_{mi}) \leq 0$ .



on other attributes that are correlated with income (e.g., if  $PAM(j)$ , and  $G(q_{mi}|q_{mj})$  is increasing in  $q_{mj}$ ). Note that this simple mechanism, which reconciles our empirical evidence with our multidimensional conceptual framework, is ruled out in one-dimensional models as it requires sorting on several different characteristics (multiple dimensions of  $q_f$  and  $q_m$ ).

## 6 Implications

This section explores broader implications of our findings for our understanding of marriage market matching. Specifically, we contrast the multidimensional matching framework (which is consistent with our empirical findings) with the commonly-used one-dimensional model under PAM (which is rejected by our evidence). In Section 6.1, we argue that our multidimensional framework offers a unifying perspective that reconciles negative sorting on earnings as predicted by Becker (1973, 1981) with model mechanisms that generate positive sorting in one-dimensional models, such as complementarities in home productivity or education homophily. In Section 6.2, we argue that our multidimensional framework suggests a strong role for sorting on unobserved characteristics. Section 6.3 illustrates the wider relevance of our findings by comparing counterfactual simulations in the one-dimensional model and a bi-dimensional specification of our framework.

### 6.1 Implications for the Interpretation of Empirical Matching Patterns

In this subsection, we revisit the widely documented positive correlation in spouses' incomes and wages, in light of our multidimensional matching framework and the evidence from establishment closures. Going back to Becker (1973, 1981), economists have interpreted this positive empirical correlation as being indicative of earnings-based positive sorting of women and men into marriages.<sup>41</sup> However, Becker's seminal theory of marriage market matching predicts positive sorting on "non-market traits" (e.g., IQ, height, attractiveness, ethnic origin), but negative sorting on wages, as this maximizes the gains from optimal division of labor in the household.<sup>42</sup>

Various arguments have been made to resolve the apparent discrepancy between the empirical positive correlation in spouses' wages and the theoretical prediction of negative sorting on wages. Becker (1973, 1981) argues that missing wage data for non-working women might bias the observed correlation between spouses' wages toward positive values. Lam (1988) shows in a simple extension of Becker's (1973, 1981) framework that joint consumption of a household public good purchased in the market may give rise to positive assortative mating.<sup>43</sup> In recent studies, complementarities in spouses' housework hours (e.g.,

<sup>41</sup>As more powerful evidence of earnings based sorting, the partial correlation in spouses' wages, controlling for years of schooling and age, has been documented to be positive, e.g., in Becker (1973, 1981).

<sup>42</sup>Becker (1981) notes that: "the strong positive partial correlation between years of schooling is predicted by the theory, but the positive correlation between wage rates is troublesome since the theory predicts a negative correlation when nonmarket productivity is held constant."

<sup>43</sup>This driver of positive assortative mating features, e.g., in Low (2024).



Gayle and Shephard 2019; Calvo et al. 2024) and homophily (e.g., Goussé et al. 2017; Gayle and Shephard 2019; Adda et al. 2024) have often been invoked to generate earnings-based positive assortative matching.

Our multidimensional matching framework (presented in Section 5) together with the evidence from establishment closures (see Section 4) offers a new perspective that allows us to reconcile Becker’s (1973,1981) prediction of negative sorting on wages with the positive empirical correlation in spouses’ wages, and with most of the model mechanisms mentioned above. Our preferred specification posits that sorting on incomes (and wages), holding all other dimensions of agent type constant, is negative. This is consistent with Becker’s (1973,1981) prediction of negative sorting on wages as an artifact of the optimal division of labor in the household. At the same time, in our framework the positive cross-sectional correlation in spouses’ wages may arise from sorting on other dimensions of agent type, e.g., from complementarities in home productivity (as in Goussé et al. 2017; Chiappori et al. 2017b and Calvo et al. 2024) or education homophily (as in Chiappori et al. 2009, 2018). Our multidimensional matching model offers a unified framework in which these model mechanisms and Becker’s (1973,1981) prediction do not contradict each other but can coexist and serve to simultaneously generate the effects consistent with our evidence from job displacements and the widely-documented positive correlation between spouses’ incomes.

## 6.2 The Role of Unobserved Characteristics in Explaining Observed Matching Patterns

In our multidimensional matching framework, the positive correlation between matched spouses’ incomes does not necessarily reflect sorting on income, but may be driven by sorting on other characteristics correlated with income. In this subsection, we decompose the correlation between spouses’ incomes into the shares driven by different observed characteristics and a residual term driven by unobserved characteristics. The arguments we invoke rely on our multidimensional matching framework (see Section 5) and conclusions drawn from our empirical findings (see Section 4).

As a starting point for the decomposition, consider the regression

$$q_{fi} = \beta_0 + \beta_1 q_{mi} + \beta_2' X_m + \beta_3' X_f + \epsilon \quad (9)$$

run on a sample of couples, where  $q_{fi}, q_{mi}$  denote husbands’ and wives’ labor incomes, and  $X_m, X_f$  are vectors of observable characteristics other than income.

Suppose that the multidimensional types that women and men match on are  $q_f = (q_{fi}, X_f, U_f)$  for women and  $q_m = (q_{mi}, X_m, U_m)$  for men, where  $X_m, X_f$  are the observed characteristics included in regression (9) and  $U_f, U_m$  are characteristics not included in the regression, which may include variables that are unobserved by us, the researchers. Regression (9) estimates the conditional mean  $\mathbb{E}[q_{fi}|q_{mi}, X_m, X_f]$ , whose dependence on  $q_{mi}$  can be decomposed as follows:

$$\mathbb{E}[q_{fi}|q_{mi}'', X_m, X_f] - \mathbb{E}[q_{fi}|q_{mi}', X_m, X_f] = \Delta_{q_{fi}} + \Delta_{U|q_{fi}},$$

where

$$\Delta_{q_{fi}} = \int \mathbb{E}[q_{fi}|q''_{mi}, X_m, U_m, X_f, U_f] - \mathbb{E}[q_{fi}|q'_{mi}, X_m, U_m, X_f, U_f] dG(U_f, U_m|q''_{mi}, X_m, X_f)$$

and

$$\begin{aligned} \Delta_{U|q_{fi}} &= \int \mathbb{E}[q_{fi}|q'_{mi}, X_m, U_m, X_f, U_f] dG(U_f, U_m|q''_{mi}, X_m, X_f) \\ &\quad - \int \mathbb{E}[q_{fi}|q'_{mi}, X_m, U_m, X_f, U_f] dG(U_f, U_m|q'_{mi}, X_m, X_f). \end{aligned}$$

The first term ( $\Delta_{q_{fi}}$ ) reflects sorting on income, keeping all other characteristics constant. The second term ( $\Delta_{U|q_{fi}}$ ) captures the indirect effect of  $q_{mi}$  on  $q_{fi}$ , via  $U_f$  and  $U_m$ .

In Section 5, we argued that in our multidimensional matching framework our quasi-experimental evidence from job displacements is consistent with NAM(i) but inconsistent with PAM(i). Under NAM(i), it can be shown that  $\Delta_{q_{fi}} \leq 0$ .<sup>44</sup> This allows us to use regression (9) to estimate a lower bound on  $\Delta_{U|q_{fi}}$ , the dependence of  $q_{fi}$  on  $q_{mi}$  that arises from sorting on  $U_f, U_m$ . Specifically, by using (9) to estimate the conditional mean  $\mathbb{E}[q_{fi}|q_{mi}, X_m, X_f]$ , and normalizing  $q''_{mi} - q'_{mi} = 1$ , it follows that  $\beta_1 \leq \Delta_{U|q_{fi}}$ . Intuitively, sorting on income, keeping other characteristics fixed, is negative under NAM(i). Sorting on characteristics not controlled for in the regression must therefore exceed the magnitude of  $\beta_1$  to rationalize the matching pattern in our data.

In Table 4, we present results from estimating regression (9), varying which observed variables are included as dependent variables in the regression (i.e., are included in  $X_m, X_f$ ) and which ones are not controlled for (i.e., are included in  $U_m, U_f$ ). The “raw” regression coefficient obtained by regressing wives’ on husbands’ income without any controls is 0.172. Controlling for age or education fixed effects for both spouses reduces the coefficient estimate by 0.018 (10.5%) and 0.083 (48.3%), respectively. Jointly controlling for age and education fixed effects reduces the estimate by 0.099 (57.6%). Given that  $\beta_1$  is a lower bound on  $\Delta_{U|q_{fi}}$ , the estimates in column (4) imply  $\Delta_{U|q_{fi}} \geq 0.073$ . I.e., at least 42.4% ( $= 0.073/0.172 \cdot 100\%$ ) of the raw coefficient is due to sorting on characteristics not controlled for in the regression (i.e., characteristics other than income, age, and education) potentially including characteristics that are typically unobserved by researchers.<sup>45</sup>

<sup>44</sup>This follows directly from the first step of the proof of Proposition 4.

<sup>45</sup>This may include characteristics that are unavailable in the Danish register data, but that other researchers have measured and studied, such as anthropometrics (Oreffice and Quintana-Domeque 2010), personality traits (Dupuy and Galichon 2014), tobacco use (Chiappori et al. 2017a) or physical attractiveness (Fisman, Iyengar, Kamenica, and Simonson 2006).

Table 4: Regressing Wives' on Husbands' Income, Controlling for Age and Education

	(1)	(2)	(3)	(4)
Husband's labor income ( $\hat{\beta}_1$ )	0.172*** (0.000521)	0.154*** (0.000523)	0.089*** (0.000539)	0.073*** (0.000541)
<i>Covariates</i>				
Male education FE	No	No	Yes	Yes
Female education FE	No	No	Yes	Yes
Male age FE	No	Yes	No	Yes
Female age FE	No	Yes	No	Yes
Observations	3,180,802	3,118,538	3,086,225	3,086,225

*Notes:* This table reports coefficient estimates of  $\beta_1$  from equation (9) for varying sets of control variables  $X_f$  and  $X_m$ . All specifications are estimated on our full sample of married or cohabiting couples, observed between 1980 and 2007. Standard errors are reported in parentheses. \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

### 6.3 Counterfactuals: The Relationship between Marital Sorting and Income Inequality

In this section, we illustrate implications of our results for the relationship between individual-level and household-level inequality, which is shaped by marital sorting. We examine how a simulated increase in individual income inequality affects between-household inequality in calibrated quantitative versions of a one-dimensional (1D) and a bidimensional (2D) specification of our framework. The simulation results show that in the one-dimensional model, which is at odds with our empirical evidence, the marriage market *amplifies* the effects of rising individual inequality on between-household inequality. In contrast, in the bidimensional model, which is consistent with our empirical findings, the marriage market *dampens* the effect of rising individual inequality on between-household inequality. These results illustrate that understanding the mechanisms underlying the positive cross-sectional income correlation—whether it directly results from income complementaries or whether it is a byproduct of sorting on other characteristics—has important implications for the relationship between marital sorting and income inequality. The nature of this relationship is relevant, e.g., for quantifying the extent to which marital sorting contributes to rising between-household inequality (Greenwood et al. 2015, 2016; Eika et al. 2019), and for understanding how redistributive taxation affects marriage decisions (see, e.g., Frankel 2014; Bronson et al. 2024; Gayle and Shephard 2019).

**Model Specification** To calibrate our framework, we make additional functional form and distributional assumptions. Our quantitative model also adds an idiosyncratic “love shock”,  $z$ , which summarizes all non-economic motives for marriage.<sup>46</sup> In the 1D model, we assume that individuals match on incomes,  $q_f$

<sup>46</sup>The love shock is drawn from a  $N(\mu_z, \sigma_z)$  distribution upon meeting a potential partner, is equal for both individuals, and is fixed for the duration of the match. The shock allows the model to generate empirically plausible matching patterns. Without the shock, income would perfectly predict (in the 1D model) whether a meeting results in a match. Jacquemet and Robin (2013), Goussé et al. (2017), and Borovicková and Shimer (2024) use similar settings.

and  $q_m$ . In the 2D model, we assume that individuals match on incomes,  $q_{f1}$  and  $q_{m1}$ , as well as a second, unobserved characteristic,  $q_{f2}$  and  $q_{m2}$ . This second dimension may be correlated with income, and we denote the correlation between income and the second, unobserved dimension by  $\rho$ .

We use the following specifications for the utility flow values of married and single individuals in the 1D and the 2D model, respectively:

$$\begin{aligned} \text{1D model:} \quad & \text{Couples: } u_g^1(q_f, q_m) = \kappa_1 \frac{(q_f + q_m)^{1-\eta}}{1-\eta} - \kappa_2 (q_f - q_m)^2 + z \\ & \text{Singles: } u_g^0(q_g) = \kappa_1 \frac{q_g^{1-\eta}}{1-\eta}, \quad g \in \{f, m\} \end{aligned} \quad (10)$$

$$\begin{aligned} \text{2D model:} \quad & \text{Couples: } u_g^1(q_f, q_m) = \omega_1 \frac{(q_{f1} + q_{m1})^{1-\eta}}{1-\eta} - \omega_2 (q_{f2} - q_{m2})^2 + z \\ & \text{Singles: } u_g^0(q_g) = \omega_1 \frac{q_{g1}^{1-\eta}}{1-\eta} \quad s \in \{f, m\}, \end{aligned} \quad (11)$$

In the 1D model, the first term on the RHS of  $u_g^1(q_f, q_m)$  induces negative sorting via the curvature of the CRRA utility term. Intuitively, the marginal utility of partner income is decreasing in own income, which is a force toward NAM. The second term on the RHS of  $u_g^1(q_f, q_m)$  penalizes non-homogamous matches and, thereby, induces positive sorting.<sup>47</sup> The magnitude of  $\kappa_2$  relative to  $\kappa_1$  determines which of the two forces dominates in the 1D model. The flow utility of singles only depends on own income and sets the non-homogamy penalty equal to zero. In the 2D model, the first term on the RHS of  $u_g^1(q_f, q_m)$  is identical to the 1D version and induces NAM on income. The second term on the RHS of  $u_g^1(q_f, q_m)$  penalizes matches that are non-homogamous in terms of the unobserved characteristic,  $q_{g2}$ , and thereby induces PAM in the second dimension. The second dimension does not matter for the flow utility of singles, which is identical to the 1D model. Additional technical details about the model (definition of type spaces, matching technology, household bargaining, equilibrium characterization, and numerical solution) are relegated to Appendix D.

**Calibration** We calibrate a 1D as well as a 2D specification of our framework. We fix five parameter values by either setting them to standard values or by estimating them outside the model. First, we fix the annual discount rate at 0.05. Second, we set the parameter that determines the curvature,  $\eta$ , equal to 1.5.<sup>48</sup> Third, we set the relationship dissolution rate,  $\delta$ , equal to 0.06, which is the annual rate at which couples break up in our sample. Fourth, we fix the Poisson meeting rate at  $\lambda = 1$ .<sup>49</sup> Fifth, we fix women's and men's Nash-bargaining power at  $\mu_f = 1 - \mu_m = 0.5$ .

<sup>47</sup>See, e.g., [Gihleb and Lang \(2016\)](#) who use a similar penalty term for non-homogamous marriages. [Marimon and Zilibotti \(2001\)](#) introduced this notion of suitability for workers and jobs in a labor market context.

<sup>48</sup>See, e.g., [Attanasio, Low, and Sánchez-Marcos \(2008\)](#).

<sup>49</sup>Recall that we assume a quadratic matching technology, implying that the meeting rates for men and women are  $\lambda_f = \lambda \int dG_m(q_m)$  and  $\lambda_m = \lambda \int dG_f(q_f)$ . Fixing the common Poisson meeting rate at  $\lambda = 1$  implies,  $\lambda_f = \int dG_m(q_m)$  and  $\lambda_m = \int dG_f(q_f)$ , i.e., the rate at which women and men meet potential partners is equal to the mass of singles of the opposite gender.

The remaining model parameters are  $\{\kappa_1, \kappa_2, \mu_z, \sigma_z\}$  in the 1D and  $\{\omega_1, \omega_2, \mu_z, \sigma_z, \rho\}$  in the 2D model. These are calibrated by minimizing the relative distance between theoretical and empirical moments. We target four common moments in both the 1D and the 2D model: the share of married individuals in the population, the marriage rate (i.e., the flow into marriage/cohabitation), the cross-sectional income correlation among couples, and the variance of log-household income.<sup>50</sup> These four moments pin down the two utility function parameters and the mean and standard deviation of the  $z$ -shock distribution. For the 2D model, to calibrate  $\rho$ , we additionally target the displacement effect estimated in Section 4.4,  $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m} = -0.25$ . Recall that this effect implies that displaced men who experience a breakup and rematch with a new partner get a 0.25 unit higher earning new partner (compared to the pre-displacement partner) for a 1 unit loss in own income. We compute the model counterpart of  $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m}$  by simulating in the model a negative exogenous income shock and measuring the average change in partner income associated with subsequent transitions to new partners. All theoretical moments are computed at the steady state. Empirical moments are computed in our estimation sample described in Section 3. We summarize all fixed and calibrated parameter values in Table B.3.

Table 5 shows the model fit. Both the 1D and the 2D version of our framework provide a good fit for the targeted empirical moments. The key difference between the models, in terms of fit, is that the 1D model predicts a positive value (0.17) for the change in partner income associated with transitioning to a new partner after job displacement,  $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m}$ , which is at odds with the data. By contrast, the 2D model is capable of matching  $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m} = -0.25$  closely. This is in line with our theoretical results presented in Sections 2 and 5.

The implied positive correlation between spousal types in the unobserved dimension,  $\text{Corr}(q_{f2}, q_{m2}) = 0.70$ , is higher than the positive correlation between spouses' incomes,  $\text{Corr}(q_{f1}, q_{m1}) = 0.22$ . This is unsurprising as the positive correlation between spouses' incomes is entirely driven by sorting on unobserved characteristics in the 2D model. The calibrated correlation between income and unobserved characteristics at the individual level, is  $\rho = 0.71$ , see Table B.3.

**Simulation Results** We use the calibrated models to simulate an increase in individual income inequality and explore how marital sorting and between-household income inequality respond in the 1D and the 2D model. We simulate an increase in income inequality by applying the following transformation to the exogenous income types, separately for men and women:

$$\tilde{q} = \max \left( c \cdot (q - \mu_{q,g}) + \mu_{q,g}, q_{\min} \right). \quad (12)$$

This transformation can be thought of as a spread around the mean of the distribution ( $\mu_{q,g}$ ), where the parameter  $c$  controls the size of the spread and the parameter  $q_{\min}$  is a small value to ensure that income remains positive. For our experiment, we set  $c = 0.15$  and  $\bar{q} = 5000$  DKK, which results in an increase

<sup>50</sup>This is a common measure of income inequality, see, e.g., [Blundell, Pistaferri, and Preston 2008](#).

Table 5: Model Fit

Moment	Value 1D Model	Value 2D Model	Empirical Value
Population share of married individuals	0.75	0.70	0.76
Income correlation, $\text{Corr}(\text{income}_f, \text{income}_m)$	0.22	0.22	0.22
Income inequality, $\text{Var}(\log(\text{income}_f + \text{income}_m))$	0.14	0.14	0.15
Marriage rate	0.04	0.04	0.05
Displacement effect, $\frac{\gamma_{\Delta q_f   R}}{\Delta q_m}$	0.17	-0.19	-0.25

*Notes:* The table shows the fit of the calibrated 1D and 2D version of our quantitative framework compared to the data. Each row corresponds to one of the 5 moments that we target in the calibration. The data moments are computed based on our sample of men who were displaced as part of an establishment closure between 1980-2007, and the same number of control individuals selected by coarsened exact matching. The specific sample selection criteria and matched sampling algorithm are described in subsection 3.3.

in the variance of income of 23% for men and 29% for women. Intuitively, increased income inequality increases the gains from marital sorting, amplifying existing patterns of sorting on income.

Table 6 contrasts the simulation results from the 1D and the 2D model. For both versions, row (1) reports simulated between-household income inequality at baseline (the calibrated steady state). Row (2) reports between-household income inequality under the counterfactual mean preserving spread, but keeping the sorting of individuals into couples fixed at baseline. Row (3) reports between-household income inequality under the counterfactual, letting both individual incomes and the sorting of individuals into couples respond.<sup>51</sup> Comparing rows (2) and (3) reveals that the 1D version of our framework—which is at odds with our empirical findings presented in Section 4—predicts that marital sorting amplifies the rise in between-household inequality. By contrast, the 2D model—which is consistent with the empirical evidence—predicts that marital sorting dampens the rise in between-household inequality. Quantitatively, under the counterfactual the 2D version of our framework predicts 30% lower between-household income inequality (0.174) compared to the 1D model (0.250).

These results highlight the relevance of our findings for understanding the relationship between marriage market sorting and income inequality. If the cross-sectional correlation between matched spouses' incomes directly arises from sorting on income (as in the 1D model) marriage market sorting can be expected to amplify between-household inequality if individual-level income inequality rises. If it is a byproduct of sorting on other characteristics while sorting on income, keeping other characteristics fixed, is negative (as in the 2D model), then marriage market sorting will dampen the effect of rising individual-level income inequality on between-household inequality. This marked difference points to potential implications of our findings for the contribution of marital sorting to between-household income inequality and for our understanding of how redistributive tax policy distorts marriage decisions by reducing income inequality.

<sup>51</sup>This includes both a change in “who marries whom” and a change in “who marries”, i.e., which model agents are married and which are singles at the steady state.

Table 6: Simulation Results: Income Inequality and Marital Sorting

	Var(log(income <sub>f</sub> + income <sub>m</sub> ))	
	1D model	2D model
(1) Baseline	0.144	0.143
(2) Counterfactual, marital sorting fixed	0.233	0.239
(3) Counterfactual	0.250	0.174

*Notes:* The table shows household income inequality, measured by the variance of log household income, in the baseline scenario (row 1) and in the counterfactual experiment that increases individual income inequality (row 3). Row 2 shows how inequality increases under the counterfactual if the sorting of individuals into couples is kept constant at the baseline distribution.

## 7 Conclusion

In this paper, we leverage exogenous variation from establishment closures to provide novel empirical evidence on marital sorting patterns. Our empirical results show that men who are displaced from their job are more likely to experience a break up, face an increased risk of remaining single post-breakup, and tend to transition away from low-earning and toward higher-earning (married or cohabiting) partners when rematching.

Standard (one-dimensional) models of marriage market matching imply a tight link between complementarities in spouses' characteristics and cross-sectional patterns of marriage market sorting. We show in a general search and matching model based on [Shimer and Smith \(2000\)](#) that our novel empirical evidence challenges this tight relationship. Specifically, we argue that our empirical findings suggest a negative association between husbands' and wives' incomes, which is consistent with negative assortative matching (NAM) but inconsistent with positive assortative matching (PAM) in one-dimensional models. By contrast, the widely documented positive correlation between spouses' incomes is consistent with PAM but contradicts NAM.

We show that theory and evidence can be reconciled in a multidimensional extension of the [Shimer and Smith \(2000\)](#) model, in which sorting on income—holding other characteristics fixed—is negative, whereas the cross-sectional positive correlation between spouses' incomes arises spuriously due to positive sorting on other characteristics that are correlated with income. We explore several additional implications of our empirical findings. First, we argue that our findings are in line with [Becker's \(1973,1981\)](#) hypothesis that husbands' and wives' earnings are substitutes, rather than complements in the marriage market. Second, we show that at least 42% of the positive association between matched spouses' earnings is due to sorting on unobserved characteristics, with the remaining 58% being due to sorting on characteristics that we observe in our data (income, age, and education). Finally, we highlight the relevance of our findings by contrasting a counterfactual increase in individual income inequality in a one-dimensional versus a bidimensional specification of our framework. The one-dimensional model (which is at odds with our



empirical evidence) predicts that marital sorting amplifies the rise in between-household income inequality. In contrast, the bidimensional model (which is consistent with our findings) predicts that marital sorting dampens the increase in between-household income inequality.

Our paper underscores the importance of understanding the mechanisms that give rise to observed cross-sectional marital sorting patterns. Does the cross-sectional correlation between spouses' incomes reflect direct sorting on income? Or is it a byproduct of sorting on other characteristics that correlate with income? Our new empirical evidence allows us to address these questions and demonstrate that the answer has implications for whether marriage market matching is one- or multidimensional, for the relative relevance of different economic mechanisms that give rise to marital sorting, and for the sign and magnitude of counterfactual simulation results in structural models of marriage market matching.

Our findings point toward several fruitful directions for future work. One promising avenue is leveraging exogenous variation in characteristics other than income (e.g., health or education) to improve our understanding of the mechanisms underlying observed cross-sectional sorting patterns in these dimensions. Another open question for future work is to what extent observed marital sorting patterns arise from complementarities in the match value, from marriage or from meeting opportunities, e.g., due to geographic segregation (Alonzo, Guner, and Luccioletti 2023), or the context in which couples meet (e.g., at work or university). Finally, our paper highlights the importance of empirically examining how policy changes, such as changes in taxation, interact with marital sorting. Studying quasi-exogenous policy changes and their effects on marital sorting would be a natural next step in this direction.

## References

- ADDA, J., P. PINOTTI, AND G. TURA (2024): "There's more to marriage than love: the effect of legal status and cultural distance on intermarriages and separations," *Journal of Political Economy*.
- ALMAR, F., B. FRIEDRICH, A. REYNOSO, B. SCHULZ, AND R. VEJLIN (2024): "Educational Ambition, Marital Sorting, and Inequality," Working paper.
- ALMAR, F. AND B. SCHULZ (2024): "Optimal Weights for Marital Sorting Measures," *Economics Letters*, 234.
- ALONZO, D., N. GUNER, AND C. LUCCIOLETTI (2023): "Segregation and Sorting of US Households: Who Marries Whom and Where?" Working paper.
- ATTANASIO, O., H. LOW, AND V. SÁNCHEZ-MARCOS (2008): "Explaining Changes in Female Labor Supply in a Life-Cycle Model," *American Economic Review*, 98, 1517–52.
- AZOULAY, P., J. S. GRAFF ZIVIN, AND J. WANG (2010): "Superstar Extinction," *The Quarterly Journal of Economics*, 125, 549–589.
- BECKER, G. S. (1973): "A Theory of Marriage: Part I," *Journal of Political Economy*, 81, 813–846.
- (1981): *A Treatise on the Family*, no. beck81-1 in NBER Books, National Bureau of Economic Research, Inc.



- BLUNDELL, R., L. PISTAFERRI, AND I. PRESTON (2008): "Consumption Inequality and Partial Insurance," *American Economic Review*, 98, 1887–1921.
- BOROVICKOVÁ, K. AND R. SHIMER (2024): "Assortative Matching and Wages: The Role of Selection," Working paper.
- BRONSON, M. A., D. HAANWINCKEL, AND M. MAZZOCCO (2024): "Taxation and household decisions: an intertemporal analysis," Tech. rep., Working Paper.
- BROWNING, M., P.-A. CHIAPPORI, AND Y. WEISS (2014): *Economics of the Family*, Cambridge Surveys of Economic Literature, Cambridge University Press.
- BROWNING, M., A. MOLLER DANO, AND E. HEINESSEN (2006): "Job displacement and stress-related health outcomes," *Health Economics*, 15, 1061–1075.
- BRUZE, G., M. SVARER, AND Y. WEISS (2015): "The dynamics of marriage and divorce," *Journal of Labor Economics*, 33, 123–170.
- CALVO, P. (2022): "The Effects of Institutional Gaps between Cohabitation and Marriage," Tech. rep., Working Paper.
- CALVO, P. A., I. LINDENLAUB, AND A. REYNOSO (2024): "Marriage Market and Labor Market Sorting," *Review of Economic Studies*.
- CHIAPPORI, P.-A. (2017): *Matching with Transfers: The Economics of Love and Marriage*, Princeton University Press.
- CHIAPPORI, P.-A., M. COSTA-DIAS, AND C. MEGHIR (2018): "The marriage market, labor supply, and education choice," *Journal of Political Economy*, 126, S26–S72.
- (2020): "Changes in Assortative Matching: Theory and Evidence for the US," Working Paper 26932, National Bureau of Economic Research.
- CHIAPPORI, P.-A., M. IYIGUN, AND Y. WEISS (2009): "Investment in Schooling and the Marriage Market," *American Economic Review*, 99, 1689–1713.
- CHIAPPORI, P.-A., S. OREFFICE, AND C. QUINTANA-DOMEQUE (2012): "Fatter Attraction: Anthropometric and Socioeconomic Matching on the Marriage Market," *Journal of Political Economy*, 120, 659–695.
- (2017a): "Bidimensional Matching with Heterogeneous Preferences: Education and Smoking in the Marriage Market," *Journal of the European Economic Association*, 16, 161–198.
- CHIAPPORI, P.-A., B. SALANIÉ, AND Y. WEISS (2017b): "Partner Choice, Investment in Children, and the Marital College Premium," *American Economic Review*, 107, 2109–67.
- CHOO, E. AND A. SIOW (2006): "Who marries whom and why," *Journal of Political Economy*, 114, 175–201.
- CISCATO, E. (2021): "The Changing Wage Distribution and the Decline of Marriage," Unpublished.
- CISCATO, E., A. GALICHON, AND M. GOUSSÉ (2020): "Like Attract Like? A Structural Comparison of Homogamy across Same-Sex and Different-Sex Households," *Journal of Political Economy*, 128, 740–781.
- COLES, M. G. AND M. FRANCESCONI (2019): "Equilibrium Search with Multiple Attributes and the Impact of Equal Opportunities for Women," *Journal of Political Economy*, 127, 138–162.

- DATTA GUPTA, N. AND M. LARSEN (2007): "Health Shocks and Retirement: The Role of Welfare State Institutions," *European Journal of Ageing*, 4, 183–190.
- DATTA GUPTA, N. AND M. LARSEN (2010): "The impact of health on individual retirement plans: Self-reported versus diagnostic measures," *Health Economics*, 19, 792–813.
- DUPUY, A. AND A. GALICHON (2014): "Personality Traits and the Marriage Market," *Journal of Political Economy*, 122, 1271–1319.
- EIKA, L., M. MOGSTAD, AND B. ZAFAR (2019): "Educational assortative mating and household income inequality," *Journal of Political Economy*, 127, 2795–2835.
- ELIASON, M. (2012): "Lost jobs, broken marriages," *Journal of Population Economics*, 25, 1365–1397.
- ELIASON, M. AND D. STORRIE (2006): "Lasting or Latent Scars? Swedish Evidence on the Long-Term Effects of Job Displacement," *Journal of Labor Economics*, 24, 831–856.
- FAGERENG, A., L. GUIISO, AND L. PISTAFERRI (2022): "Assortative Mating and Wealth Inequality," Working Paper 29903, National Bureau of Economic Research.
- FERNÁNDEZ, R., N. GUNER, AND J. KNOWLES (2005): "Love and Money: A Theoretical and Empirical Analysis of Household Sorting and Inequality\*," *The Quarterly Journal of Economics*, 120, 273–344.
- FERNÁNDEZ, R. AND J. C. WONG (2016): "Free to Leave? A Welfare Analysis of Divorce Regimes," *American Economic Journal: Macroeconomics*, 9, pp. 72–115.
- FISMAN, R., S. S. IYENGAR, E. KAMENICA, AND I. SIMONSON (2006): "Gender differences in mate selection: Evidence from a speed dating experiment," *The Quarterly Journal of Economics*, 121, 673–697.
- FRANKEL, A. (2014): "Taxation of Couples under Assortative Mating," *American Economic Journal: Economic Policy*, 6, 155–77.
- GAYLE, G.-L. AND A. SHEPHARD (2019): "Optimal Taxation, Marriage, Home Production, and Family Labor Supply," *Econometrica*, 87, 291–326.
- GIHLEB, R. AND K. LANG (2016): "Educational Homogamy and Assortative Mating Have Not Increased," Working Paper 22927, National Bureau of Economic Research.
- GOLDBERGER, A. (1991): *A Course in Econometrics*, Harvard University Press.
- GOUSSÉ, M., N. JACQUEMET, AND J.-M. ROBIN (2017): "Marriage, Labor Supply, and Home Production," *Econometrica*, 85, 1873–1919.
- GREENWOOD, J., N. GUNER, G. KOCHARKOV, AND C. SANTOS (2015): "Marry Your Like: Assortative Mating and Income Inequality (Revised Version)," *Originally Published in American Economic Review*.
- (2016): "Technology and the Changing Family: A Unified Model of Marriage, Divorce, Educational Attainment, and Married Female Labor-Force Participation," *American Economic Journal: Macroeconomics*, 8, 1–41.
- GUNER, N., Y. KULIKOVA, AND J. LLULL (2018): "Reprint of: Marriage and health: Selection, protection, and assortative mating," *European Economic Review*, 109, 162–190.

- HOLZNER, C. AND B. SCHULZ (2023): "Marriage and Divorce under Labor Market Uncertainty," Working paper.
- HUTTUNEN, K. AND J. KELLOKUMPU (2016): "The Effect of Job Displacement on Couples' Fertility Decisions," *Journal of Labor Economics*, 34, 403–442.
- IACUS, S. M., G. KING, AND G. PORRO (2012): "Causal inference without balance checking: Coarsened exact matching," *Political analysis*, 1–24.
- (2019): "A theory of statistical inference for matching methods in causal research," *Political Analysis*, 27, 46–68.
- JACOBSON, L. S., R. J. LALONDE, AND D. G. SULLIVAN (1993): "Earnings Losses of Displaced Workers," *The American Economic Review*, 83, 685–709.
- JACQUEMET, N. AND J.-M. ROBIN (2013): "Assortative matching and search with labor supply and home production," CeMMAP working papers CWP07/13, Centre for Microdata Methods and Practice, Institute for Fiscal Studies.
- JÄGER, S. AND J. HEINING (2022): "How Substitutable Are Workers? Evidence from Worker Deaths," Working Paper 30629, National Bureau of Economic Research.
- LAM, D. (1988): "Marriage Markets and Assortative Mating with Household Public Goods: Theoretical Results and Empirical Implications," *The Journal of Human Resources*, 23, 462–487.
- LAUERMANN, S., G. NÖLDEKE, AND T. TRÖGER (2020): "The Balance Condition in Search-and-Matching Models," *Econometrica*, 88, 595–618.
- LEHMANN, E. L. (1966): "Some Concepts of Dependence," *The Annals of Mathematical Statistics*, 37, 1137–1153.
- LINDENLAUB, I. AND F. POSTEL-VINAY (2021): "The Worker-Job Surplus," Working Paper 28402, National Bureau of Economic Research.
- (2023): "Multidimensional sorting under random search," *Journal of Political Economy*, 131, 3497–3539.
- LOW, C. (2024): "The Human Capital–Reproductive Capital Trade-Off in Marriage Market Matching," *Journal of Political Economy*, 132, 000–000.
- LOW, H., C. MEGHIR, L. PISTAFERRI, AND A. VOENA (2023): "Marriage, Labor Supply and the Dynamics of the Social Safety Net," Working Paper 24356, National Bureau of Economic Research.
- MARIMON, R. AND F. ZILIBOTTI (2001): "Unemployment vs. Mismatch of Talents: Reconsidering Unemployment Benefits," *The Economic Journal*, 109, 266–291.
- MORTENSEN, D. T. (2011): "Markets with search friction and the DMP model," *American Economic Review*, 101, 1073–1091.
- OREFFICE, S. AND C. QUINTANA-DOMEQUE (2010): "Anthropometry and socioeconomics among couples: Evidence in the United States," *Economics & Human Biology*, 8, 373 – 384.
- PERSSON, P. (2020): "Social insurance and the marriage market," *Journal of Political Economy*, 128, 252–300.

- PILOSSOPH, L. AND S. L. WEE (2021): "Household Search and the Marital Wage Premium," *American Economic Journal: Macroeconomics*, 13, 55–109.
- REYNOSO, A. (2024): "The impact of divorce laws on the equilibrium in the marriage market," *Journal of Political Economy*.
- SCHULZ, B. AND F. SIUDA (2023): "Marriage and Divorce: The Role of Unemployment Insurance," *Journal of Population Economics*, 36, 2277–2308.
- SHEPHARD, A. (2019): "Marriage market dynamics, gender, and the age gap," PIER Working Paper Archive 19-003, Penn Institute for Economic Research, Department of Economics, University of Pennsylvania.
- SHIMER, R. AND L. SMITH (2000): "Assortative Matching and Search," *Econometrica*, 68, 343–369.
- SULLIVAN, D. AND T. VON WACHTER (2009): "Job Displacement and Mortality: An Analysis Using Administrative Data\*," *The Quarterly Journal of Economics*, 124, 1265–1306.
- SVARER, M. (2004): "Is your love in vain? Another look at premarital cohabitation and divorce," *Journal of Human Resources*, 39, 523–535.
- WONG, L. Y. (2003a): "Structural Estimation of Marriage Models," *Journal of Labor Economics*, 21, 699–727.
- (2003b): "Why so only 5.5% of Black Men Marry White Women?" *International Economic Review*, 44, 803–826.

# Appendix

## A Proofs and Derivations

**Proof of proposition 1:** We start by proving that under PAM or NAM,  $\gamma_B \geq 0$ :

As men in the control group by definition are not displaced between period  $t_0$  and  $\tau$ , their types are unchanged between these points in time, i.e.,  $q_m(\tau) = q_m(t_0)$ . A control group couple that was matched in period  $\tau$ , therefore continues to have the identical (non-negative) marital surplus it had in  $t_0$ .

It follows that no endogenous breakups occur in the control group. Exogenous breakups, by assumption, occur at rate  $\delta$ . The overall probability that a man in the control group experiences a breakup from his  $t_0$ -partner between  $t_0$  and  $\tau$  is thus given by:

$$P(D_B = 1 | D = 0) = 1 - e^{-\delta(\tau - t_0)} \quad (\text{A.1})$$

Note that this holds under PAM as well as under NAM.

In the treatment group, by contrast, men's types change between  $t_0$  and  $\tau$  due to job displacement. Specifically,  $q_m(\tau) = q_m(t_0) - d < q_m(t_0)$ .

For a given man with pre-displacement type  $q_m(t_0)$ , job displacement will lead to a breakup if it changes the couples' marital surplus from weakly positive to negative, or equivalently if  $q_f(t_0) \in \mathcal{M}(q_m(t_0))$  but  $q_f(t_0) \notin \mathcal{M}(q_m(t_0) - d)$ .

Shimer and Smith (2000) show that under NAM or PAM matching sets are closed intervals,  $\mathcal{M}(q_m) = [a(q_m), b(q_m)]$ , with interval bounds,  $a(q_m), b(q_m)$ , that are weakly increasing in  $q_m$  under PAM and that are weakly decreasing under NAM. It follows under PAM that job displacement leads to a breakup for a man of pre-displacement type  $q_m$  if and only if he is matched with a woman of type  $q_f \in (\max\{b(q_m - d), a(q_m)\}, b(q_m)]$ .

Similarly, it follows under NAM that job displacement will lead to a breakup for a man with pre-displacement type  $q_m$  if and only if he is matched with a woman of type  $q_f \in [a(q_m), \min\{a(q_m - d), b(q_m)\})$ .

Additionally, breakups occur exogenously at rate  $\delta$  under PAM as well as under NAM.

It follows that under PAM the overall probability that a man in the treatment group experiences a breakup from his  $t_0$ -partner between  $t_0$  and  $\tau$  is given by:

$$\begin{aligned} P(D_B = 1 | D = 1) &= \underbrace{1 - e^{-\delta(\tau - t_0)}}_{\text{prob. of exogenous breakups}} \\ &+ \underbrace{\int G_f(b(q_m(t_0))) - G_f((\max\{b(q_m(t_0) - d), a(q_m(t_0))\})) dF(q_m(t_0) | D = 1)}_{\text{prob. of endogenous breakups}}. \end{aligned}$$

(A.2)

Note that  $G_f(b(q_m(t_0))) - G_f((\max\{b(q_m(t_0) - d), a(q_m(t_0))\}))$  is the mass of men of type  $q_m(t_0)$  matched with a woman of type  $q_f \in (\max\{b(q_m - d), a(q_m)\}, b(q_m)]$ , i.e., the mass of  $q_m(t_0)$ -type men who experience an endogenous breakup after displacement.

Similarly, under NAM, the overall probability that a man in the treatment group experiences a breakup from his  $t_0$ -partner between  $t_0$  and  $\tau$  is:

$$P(D_B = 1|D = 1) = \underbrace{1 - e^{-\delta(\tau - t_0)}}_{\text{prob. of exogenous breakup}} + \underbrace{\int G_f(\min\{a(q_m(t_0) - d), b(q_m(t_0))\}) - G_f(a(q_m(t_0))) dF(q_m(t_0)|D = 1)}_{\text{prob. of endogenous breakup}}, \quad (\text{A.3})$$

From (A.1), (A.2), and (A.3) it follows that under PAM as well as under NAM

$\gamma_B = P(D_B = 1|D = 1) - P(D_B = 1|D = 0) \geq 0$ . This concludes the proof of statement 1.

To see that the sign of the impact of job displacement on the probability of staying single post-breakup is undetermined, note that for a given man of type  $q_m$

$$P(D_R = 0|q_m) = \exp\left(-(\tau - t_0)\lambda_m(G_f(b(q_m)) - G_f(a(q_m)))\right).$$

It follows that  $P(D_R = 0|q_m - d) \geq P(D_R = 0|q_m)$  if and only if

$$G_f(b(q_m - d)) - G_f(b(q_m)) \geq G_f(a(q_m - d)) - G_f(a(q_m)). \quad (\text{A.4})$$

Under PAM  $a, b$  are weakly increasing in  $q_m$ , implying that  $G_f(b(q_m - d)) - G_f(b(q_m))$  is weakly negative. However, as the same is implied for  $G_f(b(q_m - d)) - G_f(b(q_m))$ , (A.4) may or may not hold. By similar arguments it follows that the sign of  $P(D_R = 0|q_m - d) \geq P(D_R = 0|q_m)$  is also undetermined under NAM.

Note that the above arguments show that for a given type  $q_m$  the sign of  $P(D_R = 0|q_m - d) - P(D_R = 0|q_m)$  is undetermined, i.e., even if the compared groups of men were to overlap perfectly (i.e., if  $F(q_m|D_B = 1, D = 1) = F(q_m|D_B = 1, D = 0)$ ) the sign of  $\gamma_{R=0|B}$  is undetermined.<sup>52</sup> In the general case,  $F(q_m|D_B = 1, D = 1) \neq F(q_m|D_B = 1, D = 0)$  is a further reason why the sign of  $\gamma_{R=0|B}$  may be weakly positive or negative. These arguments confirm statement 2.

Next, we turn to proving that under PAM the impact of job displacement on partner type,  $\gamma_{\Delta q_f|R}$ , is weakly

<sup>52</sup>The fact that even for a given individual the sign of  $P(D_R = 0|q_m - d) - P(D_R = 0|q_m)$  is undetermined implies that under additional assumptions on the stochastic ordering of  $F(q_m|D_B = 1, D = 1)$  and  $F(q_m|D_B = 1, D = 0)$ , NAM and PAM still do not determine the sign of  $\gamma_{R=0|B}$ .

negative and bounded above by

$$\bar{\gamma}_{\Delta q_f|R} = - \int_0^d \int_0^d \frac{\partial \mathbb{E}[q_f|q_m]}{\partial q_m} \Big|_{q_m=q-x} dx dF(q|D_R = 1, D_B = 1, D = 1) \leq 0.$$

Denote by  $D_\delta$  an indicator that equals 1 for men who experience an exogenous breakup between  $t_0$  and  $\tau$ , and 0 for all other men. Consider men in the treatment group of pre-displacement type  $q_m$  who separate from their  $t_0$ -partner and rematch with a new partner between  $t_0$  and  $\tau$ . The average female type this group of men is matched with in  $t_0$  can be written as weighted average:

$$\begin{aligned} & \mathbb{E}[q_f(t_0)|D_R = 1, D_B = 1, D = 1, q_m(t_0) = q_m] = \\ & \mathbb{E}[q_f(t_0)|D_R = 1, D_B = 1, D = 1, q_m, D_\delta = 1] P(D_\delta = 1|D_R = 1, D_B = 1, D = 1, q_m) \\ & + \mathbb{E}[q_f(t_0)|D_R = 1, D_B = 1, D = 1, q_m, D_\delta = 0] P(D_\delta = 0|D_R = 1, D_B = 1, D = 1, q_m) \\ & = \frac{1 - e^{-\delta(\tau-t_0)}}{1 - e^{-\delta(\tau-t_0)} + G_f(b(q_m)) - G_f(\max\{b(q_m-d), a(q_m)\})} \cdot \frac{1}{G_f(b(q_m)) - G_f(a(q_m))} \int_{a(q_m)}^{b(q_m)} q_f dG_f(q_f) \\ & + \frac{G_f(b(q_m)) - G_f(\max\{b(q_m-d), a(q_m)\})}{1 - e^{-\delta(\tau-t_0)} + G_f(b(q_m)) - G_f(\max\{b(q_m-d), a(q_m)\})} \\ & \cdot \frac{1}{G_f(b(q_m)) - G_f(\max\{b(q_m-d), a(q_m)\})} \int_{\max\{b(q_m-d), a(q_m)\}}^{b(q_m)} q_f dG_f(q_f) \\ & = \frac{1 - e^{-\delta(\tau-t_0)}}{1 - e^{-\delta(\tau-t_0)} + G_f(b(q_m)) - G_f(\max\{b(q_m-d), a(q_m)\})} \mathbb{E}[q_f|a(q_m) < q_f < b(q_m)] \\ & + \frac{G_f(b(q_m)) - G_f(\max\{b(q_m-d), a(q_m)\})}{1 - e^{-\delta(\tau-t_0)} + G_f(b(q_m)) - G_f(\max\{b(q_m-d), a(q_m)\})} \mathbb{E}[q_f|\max\{b(q_m-d), a(q_m)\} < q_f < b(q_m)] \end{aligned} \quad (\text{A.5})$$

Next we turn to computing the corresponding average for period  $\tau$ , taking into account that men in the treatment group are displaced in  $t_0$ . Their type when rematching with a new partner in  $(t_0, \tau]$  is therefore  $q_m - d$ , and the average female type they are matched with in  $\tau$  is:

$$\begin{aligned} \mathbb{E}[q_f(\tau)|D_R = 1, D_B = 1, D = 1, q_m(t_0) = q_m] &= \frac{1}{G_f(b(q_m-d)) - G_f(a(q_m-d))} \int_{a(q_m-d)}^{b(q_m-d)} q_f dG_f(q_f) \\ &= \mathbb{E}[q_f|a(q_m-d) < q_f < b(q_m-d)]. \end{aligned} \quad (\text{A.6})$$

For the control group, by contrast, as men's types are unchanged between  $t_0$  and  $\tau$ , the corresponding expressions are given by:

$$\mathbb{E}[q_f(t_0)|D_R = 1, D_B = 1, D = 0, q_m(t_0) = q_m] = \mathbb{E}[q_f(\tau)|D_R = 1, D_B = 1, D = 0, q_m(t_0) = q_m]$$



$$\begin{aligned}
&= \frac{1}{G_f(b(q_m)) - G_f(a(q_m))} \int_{a(q_m)}^{b(q_m)} q_f dG_f(q_f) \\
&= \mathbb{E}[q_f | a(q_m) < q_f < b(q_m)].
\end{aligned} \tag{A.7}$$

Using (A.5), (A.6), and (A.7) it follows for  $\gamma_{\Delta q_f|R}$  that

$$\begin{aligned}
\gamma_{\Delta q_f|R} &= \int \mathbb{E}[q_f(\tau) - q_f(t_0) | D_R = 1, D_B = 1, D = 1, q_m] dF(q_m | D_R = 1, D_B = 1, D = 1) \\
&\quad - \int \mathbb{E}[q_f(\tau) - q_f(t_0) | D_R = 1, D_B = 1, D = 0, q_m] dF(q_m | D_R = 1, D_B = 1, D = 0) \\
&= \int \frac{1 - e^{-\delta(\tau-t_0)}}{1 - e^{-\delta(\tau-t_0)} + G_f(b(q_m)) - G_f(\max\{b(q_m - d), a(q_m)\})} \\
&\quad \cdot \left( \mathbb{E}[q_f | a(q_m - d) < q_f < b(q_m - d)] - \mathbb{E}[q_f | a(q_m) < q_f < b(q_m)] \right) \\
&\quad dF(q_m | D_R = 1, D_B = 1, D = 1) \\
&\quad + \int \frac{G_f(b(q_m)) - G_f(\max\{b(q_m - d), a(q_m)\})}{1 - e^{-\delta(\tau-t_0)} + G_f(b(q_m)) - G_f(\max\{b(q_m - d), a(q_m)\})} \\
&\quad \cdot \left( \mathbb{E}[q_f | a(q_m - d) < q_f < b(q_m - d)] - \mathbb{E}[q_f | \max\{b(q_m - d), a(q_m)\} < q_f < b(q_m)] \right) \\
&\quad dF(q_m | D_R = 1, D_B = 1, D = 1) \\
&\leq \int \mathbb{E}[q_f | a(q_m - d) < q_f < b(q_m - d)] \\
&\quad - \mathbb{E}[q_f | a(q_m) < q_f < b(q_m)] dF(q_m | D_R = 1, D_B = 1, D = 1) \\
&= \int \mathbb{E}[q_f | q_m - d] - \mathbb{E}[q_f | q_m] dF(q_m | D_R = 1, D_B = 1, D = 1) \\
&= - \int \int_0^d \frac{\partial \mathbb{E}[q_f | q_m]}{\partial q_m} \Big|_{q_m=q-x} dx dF(q | D_R = 1, D_B = 1, D = 1) \\
&= \bar{\gamma}_{\Delta q_f|R},
\end{aligned}$$

where the weak inequality follows as<sup>53</sup>

$$\mathbb{E}[q_f | a(q_m) < q_f < b(q_m)] \leq \mathbb{E}[q_f | \max\{b(q_m - d), a(q_m)\} < q_f < b(q_m)]. \tag{A.8}$$

As shown by [Shimer and Smith \(2000\)](#),  $\mathbb{E}[q_f | q_m]$  is weakly increasing in  $q_m$  under PAM, from which  $\bar{\gamma}_{\Delta q_f|R} \leq 0$  follows. This concludes the proof of statements 3.-a and 3.-b.

By analogous steps it can be shown that under NAM  $\gamma_{\Delta q_f|R}$  is weakly positive and bounded below by

---

<sup>53</sup>Note that in general for any random variable  $X$ , and  $a \leq a'$  it holds that  $\mathbb{E}[X | a \leq X \leq b] \leq \mathbb{E}[X | a' \leq X \leq b]$ .

$\underline{\gamma}_{\Delta q_f|R} \geq 0$  (statements 4.-a and 4.-b).

Finally, we prove that under PAM, if  $F(q_m|D_B = 1, D = 1) \leq F(q_m|D_B = 1, D = 0)$ , then  $\gamma_{q_f|B} \geq 0$ . As noted above, under PAM  $\mathcal{M}(q_m) = [a(q_m), b(q_m)]$  with interval bounds that are weakly increasing in  $q_m$  (see Shimer and Smith (2000)). By implication, under PAM  $\mathbb{E}[q_f|a(q_m) < q_f < b(q_m)]$  is weakly increasing in  $q_m$ . From  $F(q_m|D_B = 1, D = 1) \leq F(q_m|D_B = 1, D = 0)$  it follows that<sup>54</sup>

$$\begin{aligned} & \int \mathbb{E}[q_f|a(q_m) < q_f < b(q_m)] dF(q_m|D_B = 1, D = 1) \\ & \geq \int \mathbb{E}[q_f|a(q_m) < q_f < b(q_m)] dF(q_m|D_B = 1, D = 0). \end{aligned} \quad (\text{A.9})$$

Using (A.5) and (A.7) it follows for  $\gamma_{q_f|B}$  that

$$\begin{aligned} \gamma_{q_f|B} &= \int \mathbb{E}[q_m(t_0)|D_B = 1, D = 1, q_m] dF(q_m|D_B = 1, D = 1) \\ &\quad - \int \mathbb{E}[q_m(t_0)|D_B = 1, D = 0] dF(q_m|D_B = 1, D = 0) \\ &= \int \frac{1 - e^{-\delta(\tau-t_0)}}{1 - e^{-\delta(\tau-t_0)} + G_f(b(q_m)) - G_f(\max\{b(q_m - d), a(q_m)\})} \mathbb{E}[q_f|a(q_m) < q_f < b(q_m)] \\ &\quad + \frac{G_f(b(q_m)) - G_f(\max\{b(q_m - d), a(q_m)\})}{1 - e^{-\delta(\tau-t_0)} + G_f(b(q_m)) - G_f(\max\{b(q_m - d), a(q_m)\})} \\ &\quad \mathbb{E}[q_f|\max\{b(q_m - d), a(q_m)\} < q_f < b(q_m)] dF(q_m|D_B = 1, D = 1) \\ &\quad - \int \mathbb{E}[q_f|a(q_m) < q_f < b(q_m)] dF(q_m|D_B = 1, D = 0) \\ &\geq \int \mathbb{E}[q_f|a(q_m) < q_f < b(q_m)] dF(q_m|D_B = 1, D = 1) \\ &\quad - \int \mathbb{E}[q_f|a(q_m) < q_f < b(q_m)] dF(q_m|D_B = 1, D = 0) \\ &\geq 0, \end{aligned}$$

where the first weak inequality follows by (A.8) and the second follows by (A.9). This concludes the proof of statement 5-a. Statement 5-b can be proved by analogous steps.  $\square$

**Proof of Lemma 1:** Define  $\mathcal{M}_i(q_{mi}, q_m^{-i}, q_f^{-i}) := \{q_{fi} : (q_{fi}, q_f^{-i}) \in \mathcal{M}(q_m)\}$ . We proceed by first proving that any set  $\mathcal{M}_i$  is a convex set and then show that its bounds are weakly increasing under PAM (i).<sup>55</sup>

1.  $\mathcal{M}_i(q_{mi}, q_m^{-i}, q_f^{-i})$  is convex:

<sup>54</sup>Note that in general, if  $F_1(x) \geq F_2(x)$  for all  $x$ , then  $\int h(x)dF_2(x) \geq \int h(x)dF_1(x)$  for any weakly increasing measurable function  $h(x)$ .

<sup>55</sup>Note that  $\mathcal{M}_i$  is bounded, as it is a subset of  $[\underline{q}_i, \bar{q}_i]$  by assumption.

Consider  $q'_{fi} < q''_{fi} < q'''_{fi}$ , with  $q'_{fi}$  and  $q'''_{fi}$  in  $\mathcal{M}_i(q_{mi}, q_m^{-i}, q_f^{-i})$ , i.e.,

$$(q'_{fi}, q_f^{-i}) \in \mathcal{M}(q_m), \quad (\text{A.10})$$

$$(q'''_{fi}, q_f^{-i}) \in \mathcal{M}(q_m). \quad (\text{A.11})$$

Now consider  $\mathcal{M}(q_f)$ . By A-1 there exists a  $\hat{q}_{mi}$  such that  $(\hat{q}_{mi}, q_m^{-i}) \in \mathcal{M}(q''_{fi}, q_f^{-i})$ . As matching is symmetric, equivalently:

$$(q''_{fi}, q_f^{-i}) \in \mathcal{M}(\hat{q}_{mi}, q_m^{-i}). \quad (\text{A.12})$$

In case  $\hat{q}_{mi} = q_{mi}$ , (A.12) yields  $(q''_{fi}, q_f^{-i}) \in \mathcal{M}(q_{mi}, q_m^{-i})$  and we have shown convexity of  $\mathcal{M}_i$ . Now suppose  $\hat{q}_{mi} < q_{mi}$  then PAM (i) together with (A.10) and (A.12) implies  $(q''_{fi}, q_f^{-i}) \in \mathcal{M}(q_m)$ . If  $\hat{q}_{mi} > q_{mi}$  the same follows from PAM (i), together with (A.11) and (A.12). In each case we have shown that  $(q''_{fi}, q_f^{-i}) \in \mathcal{M}(q_{mi}, q_m^{-i})$ , and thus that  $\mathcal{M}_i(q_{mi}, q_m^{-i}, q_f^{-i})$  is convex.  $\mathcal{M}_i(q_{mi}, q_m^{-i}, q_f^{-i})$  is thus an interval described by bounds  $a_i(q_{mi}, q_m^{-i}, q_f^{-i})$ ,  $b_i(q_{mi}, q_m^{-i}, q_f^{-i})$ .

2.  $a_i(q_{mi}, q_m^{-i}, q_f^{-i})$  and  $b_i(q_{mi}, q_m^{-i}, q_f^{-i})$  are weakly increasing in  $q_{mi}$  under PAM(i):

$b_i$  is weakly increasing in  $q_{mi}$ : Suppose not, then  $b_i(q'_{mi}, q_m^{-i}, q_f^{-i}) > b_i(q''_{mi}, q_m^{-i}, q_f^{-i})$  for some  $q'_{mi} < q''_{mi}$ . Note that as  $\mathcal{M}_i(q_{mi}, q_m^{-i}, q_f^{-i}) = [a_i(q_{mi}, q_m^{-i}, q_f^{-i}), b_i(q_{mi}, q_m^{-i}, q_f^{-i})]$  it follows that  $b_i(q'_{mi}, q_m^{-i}, q_f^{-i}) \in \mathcal{M}_i(q'_{mi}, q_m^{-i}, q_f^{-i})$  and  $b_i(q''_{mi}, q_m^{-i}, q_f^{-i}) \in \mathcal{M}_i(q''_{mi}, q_m^{-i}, q_f^{-i})$ . Equivalently  $(b_i(q'_{mi}, q_m^{-i}, q_f^{-i}), q_f^{-i}) \in \mathcal{M}((q'_{mi}, q_m^{-i}))$  and  $(b_i(q''_{mi}, q_m^{-i}, q_f^{-i}), q_f^{-i}) \in \mathcal{M}((q''_{mi}, q_m^{-i}))$ . By PAM(i) this constellation implies  $(b_i(q'_{mi}, q_m^{-i}, q_f^{-i}), q_f^{-i}) \in \mathcal{M}(q''_{mi}, q_m^{-i})$ . Equivalently,  $b_i(q'_{mi}, q_m^{-i}, q_f^{-i}) \in \mathcal{M}_i(q''_{mi}, q_m^{-i}, q_f^{-i})$ , in contradiction to  $b_i(q'_{mi}, q_m^{-i}, q_f^{-i})$  being the upper bound of  $\mathcal{M}_i(q'_{mi}, q_m^{-i}, q_f^{-i})$ .

That  $a_i$  is weakly increasing in  $q_{mi}$  follows by similar steps that yield,  $a_i(q'_{mi}, q_m^{-i}, q_f^{-i}) \in \mathcal{M}_i(q'_{mi}, q_m^{-i}, q_f^{-i})$ , in contradiction to  $a_i(q'_{mi}, q_m^{-i}, q_f^{-i})$  being the lower bound of  $\mathcal{M}_i(q'_{mi}, q_m^{-i}, q_f^{-i})$ .

The proof that  $a_i(q_{mi}, q_m^{-i}, q_f^{-i})$  and  $b_i(q_{mi}, q_m^{-i}, q_f^{-i})$  are weakly decreasing in  $q_{mi}$  under NAM(i) proceeds analogously.  $\square$

**Proof of Proposition 2:** We first prove that under PAM(i) or NAM(i),  $\gamma_B \geq 0$ .

As men in the control group are not displaced, their types are unchanged between  $t_0$  and  $\tau$ , i.e.,  $q_m(\tau) = q_m(t_0)$ . It follows that no endogenous breakups occur in the control group, while exogenous breakups occur at rate  $\delta$ . Like in the one-dimensional case, the probability that control group couples break up between  $t_0$  and  $\tau$  is thus given by

$$P(D_B = 1 | D = 0) = 1 - e^{-\delta(\tau - t_0)} \quad (\text{A.13})$$

under PAM as well as under NAM.

In the treatment group, the  $i$ -th dimension of men's type changes between  $t_0$  and  $\tau$  due to job displacement. Specifically,  $q_{mi}(\tau) = q_{mi}(t_0) - d < q_{mi}(\tau)$ . For a given man, with pre-displacement type  $q_m(t_0)$ , job displacement leads to a breakup if and only if  $q_f(t_0) \in \mathcal{M}((q_m^i, q_m^{-i}))$  and  $q_f(t_0) \notin \mathcal{M}((q_m^i - d, q_m^{-i}))$ . By Lemma 1, equivalently  $q_{fi} \in [a_i(q_{mi}, q_m^{-i}, q_f^{-i}), b_i(q_{mi}, q_m^{-i}, q_f^{-i})]$  and  $q_{fi} \notin [a_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), b_i(q_{mi} - d, q_m^{-i}, q_f^{-i})]$ . Further,  $a_i(q_{mi}, q_m^{-i}, q_f^{-i}), b_i(q_{mi}, q_m^{-i}, q_f^{-i})$  are weakly increasing in  $q_{mi}$  under PAM(i) and weakly decreasing in  $q_{mi}$  under NAM(i).

It follows under PAM(i) that job displacement leads to a breakup for a man of pre-displacement type  $q_m$  if and only if he is matched with a  $q_f$ -type woman, such that

$$q_{fi} \in \left( \max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\}, b_i(q_{mi}, q_m^{-i}, q_f^{-i}) \right].$$

Similarly, under NAM job displacement leads to breakup for a man of pre-displacement type  $q_m$  if and only if he is matched with a woman of type  $q_f$ , such that

$$q_{fi} \in \left[ a_i(q_{mi}, q_m^{-i}, q_f^{-i}), \max\{a_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), b_i(q_{mi}, q_m^{-i}, q_f^{-i})\} \right).$$

Additionally, breakups occur exogenously at rate  $\delta$  under PAM(i) as well as under NAM(i).

Denote by  $G_{fi}(q_{fi})$  the marginal CDF of  $q_{fi}$ , by  $G_f^{-i}(q_f^{-i})$  the joint CDF of  $q_f^{-i}$ , and by  $G_{fi}(q_{fi}|q_f^{-i})$  the marginal CDF of  $q_{fi}$  conditional on  $q_f^{-i}$ .

Under PAM(i) the overall probability that a man in the treatment group experiences a breakup between  $t_0$  and  $\tau$  is:

$$\begin{aligned} P(D_B = 1|D = 1) &= 1 - e^{-\delta(\tau-t_0)} \\ &\quad + \int \int G_{fi} \left( b_i(q_{mi}, q_m^{-i}, q_f^{-i}) | q_f^{-i} \right) \\ &\quad - G_{fi} \left( \max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\} | q_f^{-i} \right) dG_f^{-i} \left( q_f^{-i} \right) dF(q_m) \end{aligned} \quad (\text{A.14})$$

Similarly, under NAM(i) the overall probability that a man in the treatment group experiences a breakup between  $t_0$  and  $\tau$  is:

$$\begin{aligned} P(D_B = 1|D = 1) &= 1 - e^{-\delta(\tau-t_0)} \\ &\quad + \int \int G_{fi} \left( \min\{a_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), b_i(q_{mi}, q_m^{-i}, q_f^{-i})\} | q_f^{-i} \right) \\ &\quad - G_{fi} \left( a_i(q_{mi} - d, q_m^{-i}, q_f^{-i}) | q_f^{-i} \right) dG_f^{-i} \left( q_f^{-i} \right) dF(q_m). \end{aligned} \quad (\text{A.15})$$

From (A.13), (A.14), and (A.15) it follows that under PAM(i) as well as under NAM(i)

$$\gamma_B = P(D_B = 1|D = 1) - P(D_B = 1|D = 0) \geq 0, \text{ concluding the proof of statement 1.}$$

Next, we turn to proving that under PAM(i),  $\gamma_{\Delta q_{fi}} \leq 0$ .

Denote by  $D_\delta$  an indicator that equals 1 for men who experience an exogenous breakup between  $t_0$  and  $\tau$ , and 0 for all other men. Consider men in the treatment group of pre-displacement type  $q_m$ , who separate from their  $t_0$ -partner and rematch with a new partner between  $t_0$  and  $\tau$ . Moreover, condition on the  $t_0$ -partner's type in all but the  $i$ -th dimension,  $q_f^{-i}(t_0) = q_f^{-i}$ . The conditional mean of the  $t_0$ -partner's type in the  $i$ -th dimension can be written as weighted average:

$$\begin{aligned} & \mathbb{E} \left[ q_{fi}(t_0) | D_R = 1, D_B = 1, D = 1, q_m(t_0) = q_m, q_f^{-i}(t_0) = q_f^{-i} \right] = \\ & \mathbb{E} \left[ q_{fi}(t_0) | D_R = 1, D_B = 1, D = 1, q_m, q_f^{-i}, D_\delta = 1 \right] P(D_\delta = 1 | D_R = 1, D_B = 1, D = 1, q_m, q_f^{-i}) \\ & + \mathbb{E} \left[ q_{fi}(t_0) | D_R = 1, D_B = 1, D = 1, q_m, q_f^{-i}, D_\delta = 0 \right] P(D_\delta = 0 | D_R = 1, D_B = 1, D = 1, q_m, q_f^{-i}) \\ & = \frac{1 - e^{-\delta(\tau - t_0)}}{1 - e^{-\delta(\tau - t_0)} + G_{fi}(b_i(q_{mi}, q_m^{-i}, q_f^{-i}) | q_f^{-i}) - G_{fi}(\max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\} | q_f^{-i})} \\ & \cdot \frac{1}{G_{fi}(b_i(q_{mi}, q_m^{-i}, q_f^{-i}) | q_f^{-i}) - G_{fi}(a_i(q_{mi}, q_m^{-i}, q_f^{-i}) | q_f^{-i})} \int_{a_i(q_{mi}, q_m^{-i}, q_f^{-i})}^{b_i(q_{mi}, q_m^{-i}, q_f^{-i})} q_{fi} dG_{fi}(q_{fi} | q_f^{-i}) \\ & + \frac{G_{fi}(b_i(q_{mi}, q_m^{-i}, q_f^{-i}) | q_f^{-i}) - G_{fi}(\max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\} | q_f^{-i})}{1 - e^{-\delta(\tau - t_0)} + G_{fi}(b_i(q_{mi}, q_m^{-i}, q_f^{-i}) | q_f^{-i}) - G_{fi}(\max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\} | q_f^{-i})} \\ & \cdot \frac{1}{G_{fi}(b_i(q_{mi}, q_m^{-i}, q_f^{-i}) | q_f^{-i}) - G_{fi}(\max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\} | q_f^{-i})} \\ & \int_{\max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\}}^{b_i(q_{mi}, q_m^{-i}, q_f^{-i})} q_{fi} dG_{fi}(q_{fi} | q_f^{-i}) \\ & = \frac{1 - e^{-\delta(\tau - t_0)}}{1 - e^{-\delta(\tau - t_0)} + G_{fi}(b_i(q_{mi}, q_m^{-i}, q_f^{-i}) | q_f^{-i}) - G_{fi}(\max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\} | q_f^{-i})} \\ & \cdot \mathbb{E} \left[ q_{fi} | a_i(q_{mi}, q_m^{-i}, q_f^{-i}) < q_{fi} < b_i(q_{mi}, q_m^{-i}, q_f^{-i}), q_f^{-i} \right] \\ & + \frac{G_{fi}(b_i(q_{mi}, q_m^{-i}, q_f^{-i}) | q_f^{-i}) - G_{fi}(\max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\} | q_f^{-i})}{1 - e^{-\delta(\tau - t_0)} + G_{fi}(b_i(q_{mi}, q_m^{-i}, q_f^{-i}) | q_f^{-i}) - G_{fi}(\max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\} | q_f^{-i})} \\ & \cdot \mathbb{E} \left[ q_{fi} | \max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\} < q_{fi} < b_i(q_{mi}, q_m^{-i}, q_f^{-i}), q_f^{-i} \right] \end{aligned} \quad (\text{A.16})$$

Taking into account that treatment group men are displaced in period  $t_0$ , the corresponding average for

period  $\tau$  is:

$$\begin{aligned}
& \mathbb{E} \left[ q_{fi}(\tau) | D_R = 1, D_B = 1, D = 1, q_m, q_f^{-i} \right] \\
&= \frac{1}{G_{fi}(b_i(q_{mi} - d, q_m^{-i}, q_f^{-i})) - G_{fi}(a_i(q_{mi} - d, q_m^{-i}, q_f^{-i}))} \int_{a_i(q_{mi} - d, q_m^{-i}, q_f^{-i})}^{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i})} q_{fi} dG_{fi}(q_{fi} | q_f^{-i}) \\
&= \mathbb{E} \left[ q_{fi} | a_i(q_{mi} - d, q_m^{-i}, q_f^{-i}) < q_{fi} < b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), q_f^{-i} \right]. \tag{A.17}
\end{aligned}$$

For the control group, by contrast, men's types are unchanged between  $t_0$  and  $\tau$ . The corresponding expressions therefore are:

$$\begin{aligned}
& \mathbb{E} \left[ q_{fi}(t_0) | D_R = 1, D_B = 1, D = 0, q_m, q_f^{-i} \right] \\
&= \mathbb{E} \left[ q_{fi}(\tau) | D_R = 1, D_B = 1, D = 0, q_m, q_f^{-i} \right] \\
&= \frac{1}{G_{fi}(b_i(q_{mi}, q_m^{-i}, q_f^{-i})) - G_{fi}(a_i(q_{mi}, q_m^{-i}, q_f^{-i}))} \int_{a_i(q_{mi}, q_m^{-i}, q_f^{-i})}^{b_i(q_{mi}, q_m^{-i}, q_f^{-i})} q_{fi} dG_{fi}(q_{fi} | q_f^{-i}) \\
&= \mathbb{E} \left[ q_{fi} | a_i(q_{mi}, q_m^{-i}, q_f^{-i}) < q_{fi} < b_i(q_{mi}, q_m^{-i}, q_f^{-i}), q_f^{-i} \right] \tag{A.18}
\end{aligned}$$

Using (A.16), (A.23), and (A.18) it follows for  $\gamma_{\Delta q_{fi}}$  that

$$\begin{aligned}
\gamma_{\Delta q_{fi} | R} &= \int \mathbb{E} \left[ q_{fi}(\tau) - q_{fi}(t_0) | D_R = 1, D_B = 1, D = 1, q_m, q_f^{-i} \right] dG_f^{-i}(q_f^{-i}) dF(q_m | D_R = 1, D_B = 1, D = 1) \\
&\quad - \int \mathbb{E} \left[ q_{fi}(\tau) - q_{fi}(t_0) | D_R = 1, D_B = 1, D = 0, q_m, q_f^{-i} \right] dG_f^{-i}(q_f^{-i}) dF(q_m | D_R = 1, D_B = 1, D = 0) \\
&= \int \int \frac{1 - e^{-\delta(\tau - t_0)}}{1 - e^{-\delta(\tau - t_0)} + G_{fi}(b_i(q_{mi}, q_m^{-i}, q_f^{-i}) | q_f^{-i}) - G_{fi}(\max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\} | q_f^{-i})} \\
&\quad \left( \mathbb{E} \left[ q_{fi} | a_i(q_{mi} - d, q_m^{-i}, q_f^{-i}) < q_{fi} < b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), q_f^{-i} \right] - \right. \\
&\quad \left. \mathbb{E} \left[ q_{fi} | a_i(q_{mi}, q_m^{-i}, q_f^{-i}) < q_{fi} < b_i(q_{mi}, q_m^{-i}, q_f^{-i}), q_f^{-i} \right] \right) \\
&\quad + \frac{G_{fi}(b_i(q_{mi}, q_m^{-i}, q_f^{-i}) | q_f^{-i}) - G_{fi}(\max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\} | q_f^{-i})}{1 - e^{-\delta(\tau - t_0)} + G_{fi}(b_i(q_{mi}, q_m^{-i}, q_f^{-i}) | q_f^{-i}) - G_{fi}(\max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\} | q_f^{-i})} \\
&\quad \left( \mathbb{E} \left[ q_{fi} | a_i(q_{mi} - d, q_m^{-i}, q_f^{-i}) < q_{fi} < b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), q_f^{-i} \right] - \right. \\
&\quad \left. \mathbb{E} \left[ q_{fi} | \max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\} < q_{fi} < b_i(q_{mi}, q_m^{-i}, q_f^{-i}), q_f^{-i} \right] \right) \\
&\quad dG_f^{-i}(q_f^{-i}) dF(q_m | D_R = 1, D_B = 1, D = 1)
\end{aligned}$$

$$\begin{aligned}
&\leq \int \int \left( \mathbb{E} \left[ q_{fi} | a_i(q_{mi} - d, q_m^{-i}, q_f^{-i}) < q_{fi} < b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), q_f^{-i} \right] \right. \\
&\quad \left. - \mathbb{E} \left[ q_{fi} | a_i(q_{mi}, q_m^{-i}, q_f^{-i}) < q_{fi} < b_i(q_{mi}, q_m^{-i}, q_f^{-i}), q_f^{-i} \right] \right) dG_f^{-i}(q_f^{-i}) dF(q_m | D_R = 1, D_B = 1, D = 1) \\
&= \int \int \mathbb{E} \left[ q_{fi} | q_{mi} - d, q_m^{-i}, q_f^{-i} \right] - \mathbb{E} \left[ q_{fi} | q_{mi}, q_m^{-i}, q_f^{-i} \right] dG_f^{-i}(q_f^{-i}) dF(q_m | D_R = 1, D_B = 1, D = 1) \\
&= \int \int \mathbb{E} \left[ q_{fi} | q_{mi} - d, q_m^{-i}, q_f^{-i} \right] - \mathbb{E} \left[ q_{fi} | q_{mi}, q_m^{-i}, q_f^{-i} \right] dG_f^{-i}(q_f^{-i}) dF(q_m | D_R = 1, D_B = 1, D = 1) \\
&= - \int \int \int_0^d \frac{\partial \mathbb{E} \left[ q_{fi} | q_{mi}, q_m^{-i}, q_f^{-i} \right]}{\partial q_{mi}} \Big|_{q_{mi}=q-x} dx dG_f^{-i}(q_f^{-i}) dF(q | D_R = 1, D_B = 1, D = 1) \\
&= \bar{\gamma}_{\Delta q_{fi}|R},
\end{aligned}$$

where the weak inequality follows as

$$\begin{aligned}
&\mathbb{E} \left[ q_{fi} | a_i(q_{mi}, q_m^{-i}, q_f^{-i}) < q_{fi} < b_i(q_{mi}, q_m^{-i}, q_f^{-i}), q_f^{-i} \right] \\
&\leq \mathbb{E} \left[ q_{fi} | \max\{b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), a_i(q_{mi}, q_m^{-i}, q_f^{-i})\} < q_{fi} < b_i(q_{mi} - d, q_m^{-i}, q_f^{-i}), q_f^{-i} \right]. \quad (\text{A.19})
\end{aligned}$$

By Lemma 1 under PAM(i)

$$\mathbb{E} \left[ q_{fi} | q_{mi}, q_m^{-i}, q_f^{-i} \right] = \mathbb{E} \left[ q_{fi} | a_i(q_{mi}, q_m^{-i}, q_f^{-i}) < q_{fi} < b_i(q_{mi}, q_m^{-i}, q_f^{-i}), q_f^{-i} \right]$$

is weakly increasing in  $q_{mi}$ , from which  $\bar{\gamma}_{\Delta q_{fi}|R} \leq 0$  follows. This concludes the proof of statements 3.-a and 3.-b.

By analogous steps it can be shown that under NAM(i)  $\gamma_{\Delta q_{fi}|R}$  is weakly positive and bounded below by  $\bar{\gamma}_{\Delta q_{fi}|R} \geq 0$  (statements 4.-a and 4.-b).  $\square$

**Lemma 2.** *Given the assumptions of Lemma 1 and A-2, under PAM(j) or NAM(j)*

$$\{q_{fi} : (q_{fi}, q_f^{-i}) \in \mathcal{M}(q_m)\} = [a_i(q_{mi}, q_{mj}, q_m^{-i,j}, q_f^{-i}), b_i(q_{mi}, q_{mj}, q_m^{-i,j}, q_f^{-i})],$$

where  $a_i, b_i$  are

(i) increasing in  $q_{mj}$  under PAM(j),

(ii) decreasing in  $q_{mj}$  under NAM(j).

**Proof of Lemma 2:** We start by proving that for any  $q'_{fi} < q''_{fi}$ ,  $q'_{mj} < q''_{mj}$ ,  $q_f^{-i}$ , and  $q_m^{-j}$ :

$$(q'_{fi}, q_f^{-i}) \in \mathcal{M}(q''_{mj}, q_m^{-j}) \text{ and } (q''_{fi}, q_f^{-i}) \in \mathcal{M}(q'_{mj}, q_m^{-j})$$



$$\Rightarrow (q'_{fi}, q_f^{-i}) \in \mathcal{M}(q'_{mj}, q_m^{-j}) \text{ and } (q''_{fi}, q_f^{-i}) \in \mathcal{M}(q''_{mj}, q_m^{-j}). \quad (\text{A.20})$$

Under PAM(j) it follows by Lemma 1 that:

$$(q'_{fi}, q_f^{-i}) \in \mathcal{M}(q''_{mj}, q_m^{-j}) \Leftrightarrow q_{fj} \in [a_j(q'_{mj}, q_m^{-j}, q'_{fi}, q_f^{-i,j}), b_j(q'_{mj}, q_m^{-j}, q'_{fi}, q_f^{-i,j})],$$

with  $a_j, b_j$  weakly increasing in  $q_{mj}$ . It follows that  $a_j(q'_{mj}, q_m^{-j}, q'_{fi}, q_f^{-i,j}) \leq a_j(q''_{mj}, q_m^{-j}, q'_{fi}, q_f^{-i,j})$ . In the special case  $q_{fj} = a_j(q'_{mj}, q_m^{-j}, q'_{fi}, q_f^{-i,j})$ , it follows trivially that  $(q'_{fi}, q_f^{-i}) \in \mathcal{M}(q'_{mj}, q_m^{-j})$ . Outside this special case, it holds that  $a_j(q'_{mj}, q_m^{-j}, q'_{fi}, q_f^{-i,j}) < q_{fj}$ . It follows that there exists a  $\check{q}_{fj} < q_{fj}$  such that  $\check{q}_{fj} \in [a_j(q'_{mj}, q_m^{-j}, q'_{fi}, q_f^{-i,j}), b_j(q'_{mj}, q_m^{-j}, q'_{fi}, q_f^{-i,j})]$ , or equivalently  $(q'_{fi}, \check{q}_{fj}, q_f^{-i,j}) \in \mathcal{M}(q'_{mj}, q_m^{-j})$ . Together with  $(q''_{fi}, q_{fj}, q_f^{-i,j}) \in \mathcal{M}(q'_{mj}, q_m^{-j})$  by A-2,  $(q'_{fi}, q_f^{-i}) \in \mathcal{M}(q'_{mj}, q_m^{-j})$  is implied (the first part of the right hand side of implication A.20).

By analogous steps, using PAM(j) together with Lemma 1 and A-2, it can be shown that  $(q''_{fi}, q_f^{-i}) \in \mathcal{M}(q'_{mj}, q_m^{-j})$  implies  $(q'_{fi}, q_f^{-i}) \in \mathcal{M}(q''_{mj}, q_m^{-j})$ , proving the second part of implication A.20.

By Lemma 1 we have

$$\mathcal{M}_i(q_{mi}, q_{mj}, q_m^{-i,j}, q_f^{-i}) = [a_i(q_{mi}, q_{mj}, q_m^{-i,j}, q_f^{-i}), b_i(q_{mi}, q_{mj}, q_m^{-i,j}, q_f^{-i})]$$

for  $\mathcal{M}_i(q_{mi}, q_m^{-i}, q_f^{-i}) := \{q_{fi} : (q_{fi}, q_f^{-i}) \in \mathcal{M}(q_m)\}$ . Next, we use A.20 to show that under PAM(j)  $b_i$  is weakly increasing in  $q_{mj}$ : Suppose not, then  $b_i(q_{mi}, q'_{mj}, q_m^{-i,j}, q_f^{-i}) > b_i(q_{mi}, q''_{mj}, q_m^{-i,j}, q_f^{-i})$  for some  $q'_{mj} < q''_{mj}$ .

From  $\mathcal{M}_i(q_{mi}, q_{mj}, q_m^{-i,j}, q_f^{-i}) = [a_i(q_{mi}, q_{mj}, q_m^{-i,j}, q_f^{-i}), b_i(q_{mi}, q_{mj}, q_m^{-i,j}, q_f^{-i})]$  it follows that  $b_i(q_{mi}, q'_{mj}, q_m^{-i,j}, q_f^{-i}) \in \mathcal{M}_i(q_{mi}, q'_{mj}, q_m^{-i,j}, q_f^{-i})$  and  $b_i(q_{mi}, q''_{mj}, q_m^{-i,j}, q_f^{-i}) \in \mathcal{M}_i(q_{mi}, q''_{mj}, q_m^{-i,j}, q_f^{-i})$ . Equivalently,  $(b_i(q_{mi}, q'_{mj}, q_m^{-i,j}, q_f^{-i}), q_f^{-i}) \in \mathcal{M}((q_{mi}, q'_{mj}, q_m^{-i,j}))$  and  $(b_i(q_{mi}, q''_{mj}, q_m^{-i,j}, q_f^{-i}), q_f^{-i}) \in \mathcal{M}((q_{mi}, q''_{mj}, q_m^{-i,j}))$ .

By A.20 this constellation implies  $(b_i(q_{mi}, q'_{mj}, q_m^{-i,j}, q_f^{-i}), q_f^{-i}) \in \mathcal{M}((q_{mi}, q''_{mj}, q_m^{-i,j}))$ , or equivalently,  $b_i(q_{mi}, q'_{mj}, q_m^{-i,j}, q_f^{-i}) \in \mathcal{M}_i(q_{mi}, q''_{mj}, q_m^{-i,j}, q_f^{-i})$ , in contradiction to  $b_i(q_{mi}, q''_{mj}, q_m^{-i,j}, q_f^{-i})$  being the upper bound of  $\mathcal{M}_i(q_{mi}, q''_{mj}, q_m^{-i,j}, q_f^{-i})$ .

By similar steps it can be shown that  $a_i$  is weakly increasing in  $q_{mj}$ .

The proof that  $a_i, b_i$  are weakly decreasing in  $q_{mj}$  under NAM(j) proceeds analogously.  $\square$

**Proof of Proposition 3:** We first show that PAM(i) implies  $DE \geq 0$ . By Lemma 1

$$\mathbb{E}[q_{fi} | q_{mi}, q_{mj}, q_{fj}] = \frac{1}{G_{fi}(b_i(q_{mi}, q_{mj}, q_{fj})) - G_{fi}(a_i(q_{mi}, q_{mj}, q_{fj}))} \int_{a_i(q_{mi}, q_{mj}, q_{fj})}^{b_i(q_{mi}, q_{mj}, q_{fj})} q_{fi} dG_{fi}(q_{fi} | q_{fj})$$

$$= \mathbb{E} [q_{fi} | a_i(q_{mi}, q_{mj}, q_{fj}) < q_{fi} < b_i(q_{mi}, q_{mj}, q_{fj}), q_{fj}] .$$

where, under PAM(i),  $a_i(q_{mi}, q_{mj}, q_{fj})$  and  $b_i(q_{mi}, q_{mj}, q_{fj})$  are weakly increasing in  $q_{mi}$  implying the same for  $\mathbb{E} [q_{fi} | q_{mi}, q_{mj}, q_{fj}]$ . It follows that

$$E[q_{fi} | q_{mi}, q_{mj}] = \int \mathbb{E} [q_{fi} | a_i(q_{mi}, q_{mj}, q_{fj}) < q_{fi} < b_i(q_{mi}, q_{mj}, q_{fj}), q_{fj}] dG_{fj}(q_{fj})$$

is also weakly increasing in  $q_{mi}$ , and

$$DE = \int E[q_{fi} | q''_{mi}, q_{mj}] - E[q_{fi} | q'_{mi}, q_{mj}] dG_{mj}(q_{mj} | q''_{mi}) \geq 0.$$

By analogous steps it follows that NAM(i) implies  $DE \leq 0$ .

Next, we establish that under PAM(j) if  $G_{mj}(q_{mj} | q_{mi})$  is weakly decreasing in  $q_{mi}$ ,  $IE \geq 0$  follows. By Lemma 1

$$\mathbb{E} [q_{fi} | q_{mi}, q_{mj}, q_{fj}] = \mathbb{E} [q_{fi} | a_i(q_{mi}, q_{mj}, q_{fj}) < q_{fi} < b_i(q_{mi}, q_{mj}, q_{fj}), q_{fj}] .$$

By Lemma 2  $a_i(q_{mi}, q_{mj}, q_{fj})$  and  $b_i(q_{mi}, q_{mj}, q_{fj})$  are weakly increasing in  $q_{mj}$  under PAM (j), implying the same for  $\mathbb{E} [q_{fi} | q_{mi}, q_{mj}, q_{fj}]$ . It follows that

$$E[q_{fi} | q_{mi}, q_{mj}] = \int \mathbb{E} [q_{fi} | a_i(q_{mi}, q_{mj}, q_{fj}) < q_{fi} < b_i(q_{mi}, q_{mj}, q_{fj}), q_{fj}] dG_{fj}(q_{fj})$$

weakly increasing in  $q_{mj}$ . As  $G(q_{mj} | q''_{mi})$  first order stochastically dominates  $G(q_{mj} | q'_{mi})$  this implies

$$IE = \int \mathbb{E} [q_{fi} | q'_{mi}, q_{mj}] dG(q_{mj} | q''_{mi}) - \int \mathbb{E} [q_{fi} | q'_{mi}, q_{mj}] dG(q_{mj} | q'_{mi}) \geq 0.$$

The remaining implications for  $IE$  follow analogously. □

**Proposition 4.** Consider the described matching environment in the multidimensional case,  $K > 1$  and suppose that A-1 and A-2 hold. Consider the following decomposition for  $q''_{mi} \geq q'_{mi}$

$$\begin{aligned}
\mathbb{E}[q_{fi}|q''_{mi}] &= \mathbb{E}[q_{fi}|q'_{mi}] \\
&= \underbrace{\int \mathbb{E}[q_{fi}|q''_{mi}, q_m^{-i}] - \mathbb{E}[q_{fi}|q'_{mi}, q_m^{-i}] dG(q_m^{-i}|q''_{mi})}_{=DE \text{ (Direct effect)}} \\
&+ \sum_{k \neq i} \left( \underbrace{\int \int \mathbb{E}[q_{fi}|q'_{mi}, q_m^{-i}] dG(q_{m,1:k-1} \setminus \{i\} | q_{m,k:K} \setminus \{i\}, q'_{mi}) dG(q_{mk} | q_{m,k+1:K} \setminus \{i\}, q''_{mi})}_{\dots} \right. \\
&\quad \left. - \underbrace{\int \int \mathbb{E}[q_{fi}|q'_{mi}, q_m^{-i}] dG(q_{m,1:k-1} \setminus \{i\} | q_{m,k:K} \setminus \{i\}, q'_{mi}) dG(q_{mk} | q_{m,k+1:K} \setminus \{i\}, q'_{mi})}_{:=IE_k \text{ (Indirect effect from k-th dimension)}} \right. \\
&\quad \left. \underbrace{dG(q_{m,k+1:K} \setminus \{i\} | q''_{mi})}_{\dots} \right).
\end{aligned}$$

In a multi-dimensional steady state matching equilibrium the following implications hold:

$$PAM(i) \Rightarrow DE \geq 0,$$

$$NAM(i) \Rightarrow DE \leq 0$$

Given  $PAM(j)$  for  $j \in A_{PAM}$  and  $NAM(j)$  for  $j \in A_{NAM}$ , where  $A_{PAM} \cup A_{NAM} = \{1, \dots, K\}$ , the following additional implications hold.<sup>56</sup>

$$\left. \begin{aligned}
(i) & PAM(k) \text{ and } G(q_{mk} | q_{m,k+1:K} \setminus \{i\}, q_{mi}) \text{ is weakly decreasing in } q_{mi}. \\
(ii) & G(q_{m,A_{PAM} \setminus \{i,k:K\}} | q_{m,A_{NAM} \setminus \{i,k:K\}}, q_{mk}, q_{m,k+1:K} \setminus \{i\}, q_{mi}) \text{ is weakly decreasing in } q_{mk}, \\
& \text{and weakly increasing in } q_{m,A_{NAM} \setminus \{i,k:K\}}. \\
(iii) & G(q_{m,A_{NAM} \setminus \{i,k:K\}} | q_{m,A_{PAM} \setminus \{i,k:K\}}, q_{mk}, q_{m,k+1:K} \setminus \{i\}, q_{mi}) \text{ is weakly increasing in } q_{mk}, \\
& \text{and weakly increasing in } q_{m,A_{PAM} \setminus \{i,k:K\}}.
\end{aligned} \right\} \Rightarrow IE_k \geq 0, \quad (A.21)$$

$$\left. \begin{aligned}
(i) & NAM(k) \text{ and } G(q_{mk} | q_{m,k+1:K} \setminus \{i\}, q_{mi}) \text{ is weakly decreasing in } q_{mi}. \\
(ii) & G(q_{m,A_{PAM} \setminus \{i,k:K\}} | q_{m,A_{NAM} \setminus \{i,k:K\}}, q_{mk}, q_{m,k+1:K} \setminus \{i\}, q_{mi}) \text{ is weakly increasing in } q_{mk}, \\
& \text{and weakly increasing in } q_{m,A_{NAM} \setminus \{i,k:K\}}. \\
(iii) & G(q_{m,A_{NAM} \setminus \{i,k:K\}} | q_{m,A_{PAM} \setminus \{i,k:K\}}, q_{mk}, q_{m,k+1:K} \setminus \{i\}, q_{mi}) \text{ is weakly decreasing in } q_{mk}, \\
& \text{and weakly increasing in } q_{m,A_{PAM} \setminus \{i,k:K\}}.
\end{aligned} \right\} \Rightarrow IE_k \leq 0, \quad (A.22)$$

<sup>56</sup>Note that analogous sufficient conditions for  $IE_k \geq 0$  and  $IE_k \leq 0$  can be proved assuming in the antecedent that  $G(q_{mk} | q_{m,k+1:K} \setminus \{i\}, q_{mi})$  is weakly increasing in  $q_{mi}$ . We omit these additional implications for brevity.

**Proof of Proposition 4:** We first show that PAM(i) implies  $DE \geq 0$ . By Lemma 1

$$\begin{aligned}\mathbb{E}[q_{fi}|q_{mi}, q_m^{-i}, q_f^{-i}] &= \frac{1}{G_{fi}(b_i(q_{mi}, q_m^{-i}, q_f^{-i})) - G_{fi}(a_i(q_{mi}, q_m^{-i}, q_f^{-i}))} \int_{a_i(q_{mi}, q_m^{-i}, q_f^{-i})}^{b_i(q_{mi}, q_m^{-i}, q_f^{-i})} q_{fi} dG_{fi}(q_{fi}|q_f^{-i}) \\ &= \mathbb{E}[q_{fi}|a_i(q_{mi}, q_m^{-i}, q_f^{-i}) < q_{fi} < b_i(q_{mi}, q_m^{-i}, q_f^{-i}), q_f^{-i}].\end{aligned}$$

where, under PAM(i),  $a_i(q_{mi}, q_m^{-i}, q_f^{-i})$  and  $b_i(q_{mi}, q_m^{-i}, q_f^{-i})$  are weakly increasing in  $q_{mi}$  implying the same for  $\mathbb{E}[q_{fi}|q_{mi}, q_m^{-i}, q_f^{-i}]$ . It follows that

$$E[q_{fi}|q_{mi}, q_m^{-i}] = \int \mathbb{E}[q_{fi}|a_i(q_{mi}, q_m^{-i}, q_f^{-i}) < q_{fi} < b_i(q_{mi}, q_m^{-i}, q_f^{-i}), q_f^{-i}] dG_{fj}(q_f^{-i})$$

is also weakly increasing in  $q_{mi}$ , and

$$DE = \int E[q_{fi}|q_{mi}'', q_m^{-i}] - E[q_{fi}|q_{mi}', q_m^{-i}] dG_{mj}(q_m^{-i}|q_{mi}'') \geq 0.$$

By analogous steps it follows that NAM(i) implies  $DE \leq 0$ .

Next, we assume that  $PAM(j)$  for  $j \in A_{PAM}$  and  $NAM(j)$  for  $j \in A_{NAM}$ , where  $A_{PAM} \cup A_{NAM} = \{1, \dots, K\}$ , and establish that  $IE_k \geq 0$  follows from premise (i) - (iii) of implication (A.21).

Note that  $IE_k$  can be expressed as

$$\begin{aligned}IE_k &= \int \int \int \mathbb{E}[q_{fi}|q_{mi}', q_m^{-i}] dG(q_{m, A_{PAM} \setminus \{i, k: K\}} | q_{m, A_{NAM} \setminus \{i, k: K\}}, q_{mk}, q_{m, k+1: K \setminus \{i\}}, q_{mi}') \\ &\quad dG(q_{m, A_{NAM} \setminus \{i, k: K\}} | q_{mk}, q_{m, k+1: K \setminus \{i\}}, q_{mi}') dG(q_{mk} | q_{m, k+1: K \setminus \{i\}}, q_{mi}'') \\ &- \int \int \mathbb{E}[q_{fi}|q_{mi}'', q_m^{-i}] dG(q_{m, A_{PAM} \setminus \{i, k: K\}} | q_{m, A_{NAM} \setminus \{i, k: K\}}, q_{mk}, q_{m, k+1: K \setminus \{i\}}, q_{mi}'') \\ &\quad dG(q_{m, A_{NAM} \setminus \{i, k: K\}} | q_{mk}, q_{m, k+1: K \setminus \{i\}}, q_{mi}'') dG(q_{mk} | q_{m, k+1: K \setminus \{i\}}, q_{mi}'') dG(q_{m, k+1: K \setminus \{i\}} | q_{mi}'')\end{aligned}$$

By Lemma 1

$$\mathbb{E}[q_{fi}|q_{mi}, q_m^{-i}] = \int \mathbb{E}[q_{fi}|a_i(q_{mi}, q_m^{-i}, q_f^{-i}) < q_{fi} < b_i(q_{mi}, q_m^{-i}, q_f^{-i}), q_f^{-i}] dG_{fj}(q_f^{-i}).$$

By Lemma 2  $a_i(q_{mi}, q_m^{-i}, q_f^{-i})$  and  $b_i(q_{mi}, q_m^{-i}, q_f^{-i})$  are weakly increasing in  $q_{mj}$  for all  $j \in A_{PAM}$ , and weakly decreasing in  $q_{mj}$  for all  $j \in A_{NAM}$ , implying the same for  $\mathbb{E}[q_{fi}|q_{mi}, q_m^{-i}]$ .

By the premise,  $G(q_{m, A_{PAM} \setminus \{i, k: K\}} | q_{m, A_{NAM} \setminus \{i, k: K\}}, q_{mk}, q_{m, k+1: K \setminus \{i\}}, q_{mi})$  is weakly decreasing in  $q_{mk}$  and weakly increasing in  $q_{m, A_{NAM} \setminus \{i, k: K\}}$ . It follows that for any  $q_{mk}' \leq q_{mk}''$  and  $q_{m, A_{NAM} \setminus \{i, k: K\}}' \leq q_{m, A_{NAM} \setminus \{i, k: K\}}''$

$$\begin{aligned}&\int \mathbb{E}[q_{fi}|q_{mi}', q_m^{-i}] dG(q_{m, A_{PAM} \setminus \{i, k: K\}} | q_{m, A_{NAM} \setminus \{i, k: K\}}'', q_{mk}', q_{m, k+1: K \setminus \{i\}}, q_{mi}') \\ &\leq \int \mathbb{E}[q_{fi}|q_{mi}'', q_m^{-i}] dG(q_{m, A_{PAM} \setminus \{i, k: K\}} | q_{m, A_{NAM} \setminus \{i, k: K\}}', q_{mk}'', q_{m, k+1: K \setminus \{i\}}, q_{mi}''),\end{aligned}$$

by  $\mathbb{E}[q_{fi}|q_{mi}, q_m^{-i}]$  being weakly increasing in  $q_{m, A_{PAM} \setminus \{i, k: K\}}$ , weakly decreasing in  $q_{m, A_{NAM} \setminus \{i, k: K\}}$ , and by first order stochastic dominance of  $G(q_{m, A_{PAM} \setminus \{i, k: K\}}|q'_{m, A_{NAM} \setminus \{i, k: K\}}, q''_{mk}, q_{m, k+1:K \setminus \{i\}}, q'_{mi})$  over  $G(q_{m, A_{PAM} \setminus \{i, k: K\}}|q''_{m, A_{NAM} \setminus \{i, k: K\}}, q'_{mk}, q_{m, k+1:K \setminus \{i\}}, q'_{mi})$ , implying that

$$\int \mathbb{E}[q_{fi}|q'_{mi}, q_m^{-i}] dG(q_{m, A_{PAM} \setminus \{i, k: K\}}|q_{m, A_{NAM} \setminus \{i, k: K\}}, q_{mk}, q_{m, k+1:K \setminus \{i\}}, q'_{mi}) \quad (\text{A.23})$$

is weakly increasing in  $q_{mk}$ , and weakly decreasing in  $q_{m, A_{NAM} \setminus \{i, k: K\}}$ .

By analogous arguments it follows from  $G(q_{m, A_{NAM} \setminus \{i, k: K\}}|q_{m, A_{PAM} \setminus \{i, k: K\}}, q_{mk}, q_{m, k+1:K \setminus \{i\}}, q_{mi})$  being weakly increasing in  $q_{mk}$ , and by (A.23) being weakly decreasing in  $q_{mk}$ , and weakly decreasing in  $q_{m, A_{NAM} \setminus \{i, k: K\}}$  that

$$\begin{aligned} & \int \int \mathbb{E}[q_{fi}|q'_{mi}, q_m^{-i}] dG(q_{m, A_{PAM} \setminus \{i, k: K\}}|q_{m, A_{NAM} \setminus \{i, k: K\}}, q_{mk}, q_{m, k+1:K \setminus \{i\}}, q'_{mi}) \\ & dG(q_{m, A_{NAM} \setminus \{i, k: K\}}|q_{mk}, q_{m, k+1:K \setminus \{i\}}, q'_{mi}) \end{aligned} \quad (\text{A.24})$$

is weakly increasing in  $q_{mk}$ .

By the premise,  $G(q_{mk}|q_{m, k+1:K \setminus \{i\}}, q''_{mi})$  first order stochastically dominates  $G(q_{mk}|q_{m, k+1:K \setminus \{i\}}, q'_{mi})$ , implying together with (A.24) being weakly increasing in  $q_{mk}$  that

$$\begin{aligned} & \int \int \mathbb{E}[q_{fi}|q'_{mi}, q_m^{-i}] dG(q_{m, A_{PAM} \setminus \{i, k: K\}}|q_{m, A_{NAM} \setminus \{i, k: K\}}, q_{mk}, q_{m, k+1:K \setminus \{i\}}, q'_{mi}) \\ & dG(q_{m, A_{NAM} \setminus \{i, k: K\}}|q_{mk}, q_{m, k+1:K \setminus \{i\}}, q'_{mi}) dG(q_{mk}|q_{m, k+1:K \setminus \{i\}}, q''_{mi}) \\ & - \int \int \mathbb{E}[q_{fi}|q'_{mi}, q_m^{-i}] dG(q_{m, A_{PAM} \setminus \{i, k: K\}}|q_{m, A_{NAM} \setminus \{i, k: K\}}, q_{mk}, q_{m, k+1:K \setminus \{i\}}, q'_{mi}) \\ & dG(q_{m, A_{NAM} \setminus \{i, k: K\}}|q_{mk}, q_{m, k+1:K \setminus \{i\}}, q'_{mi}) dG(q_{mk}|q_{m, k+1:K \setminus \{i\}}, q'_{mi}) \geq 0 \end{aligned} \quad (\text{A.25})$$

As (A.25) is satisfied for any  $q_{m, k+1:K \setminus \{i\}}$ , integrating over  $G(q_{m, k+1:K \setminus \{i\}}|q''_{mi})$  preserves the weak inequality, implying  $IE_k \geq 0$ .

Implication (A.22) can be proved by analogous steps. □

## B Additional Tables

Table B.1: Pre-displacement Summary Statistics, Treatment and Control Group

	Treatment	Control
Age	38.1 (36.2)	38.1 (36.2)
Partner's age	36.2 (12.6)	36.2 (12.6)
Years of education	12.6 (2.4)	12.6 (2.4)
Partner's years of education	12.2 (2.4)	12.3 (2.4)
Job tenure	6.4 (4.1)	6.4 (4.0)
No. of children	1.5 (1.0)	1.5 (1.0)
Labor income (in DKK)	326,247 (97021)	324,898 (96761)
Partner's labor income (in DKK)	177,682 (106798)	178,891 (106877)
Corr(age <sub>f</sub> , age <sub>m</sub> )	0.83	0.83
Corr(education <sub>f</sub> , education <sub>m</sub> )	0.38	0.39
Corr(income <sub>f</sub> , income <sub>m</sub> )	0.15	0.15
<i>N</i>	72,667	72,667

*Notes:* This table shows summary statistics for the actual and placebo displaced men in the treatment and control group. Standard deviations are reported in parentheses. All variables are measured in  $t = -1$ , i.e., one year before actual or placebo displacement. Years of education are calculated as follows: 9 years for individuals with compulsory education, 12 years for individuals with a high school degree ("Gymnasium"), 13 years for individuals with a vocational degree, 13.5 years for individuals with a degree from professional schools or technical colleges ("Professionsbachelor"), 15 years for individuals with a Bachelor's degree, and 18.5 years for individuals with a Master's or Doctoral degree. Tenure measures the years of employment at the establishment. Labor incomes are real annual labor earnings in DKK (2004 CPI).

Table B.2: Impact of Job Displacement on the Risk of Staying Single

	$P(\text{matched}_{t+1}   \text{single}_t)$	$P(\text{matched}_{t>t^*}   \text{single}_{t^*>-3})$
Control group	0.12	0.62
$\Delta$ Treatment - Control	-0.0044** (0.0015)	-0.0113** (0.0054)
Percentage difference	-3.6%	-1.8%
No. of observations	95,157	33,296

*Notes:* This table reports differences between actual and placebo displaced men in the probability of being matched with a partner in  $t + 1$  conditional having been single in  $t$  (in column 1), and in the probability of being matched with a partner at some point in time  $t > t^*$  after having been single in at least one time period,  $t^* > -3$  (in column 2). For each comparison we start from our sample of 72,667 displaced men and the same number of placebo displaced individuals observed over our event-time window  $t = -5, \dots, 10$ , and select all individual  $\times t$  observations in the respective conditioning set. Standard errors are reported in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table B.3: Calibrated Parameter Values

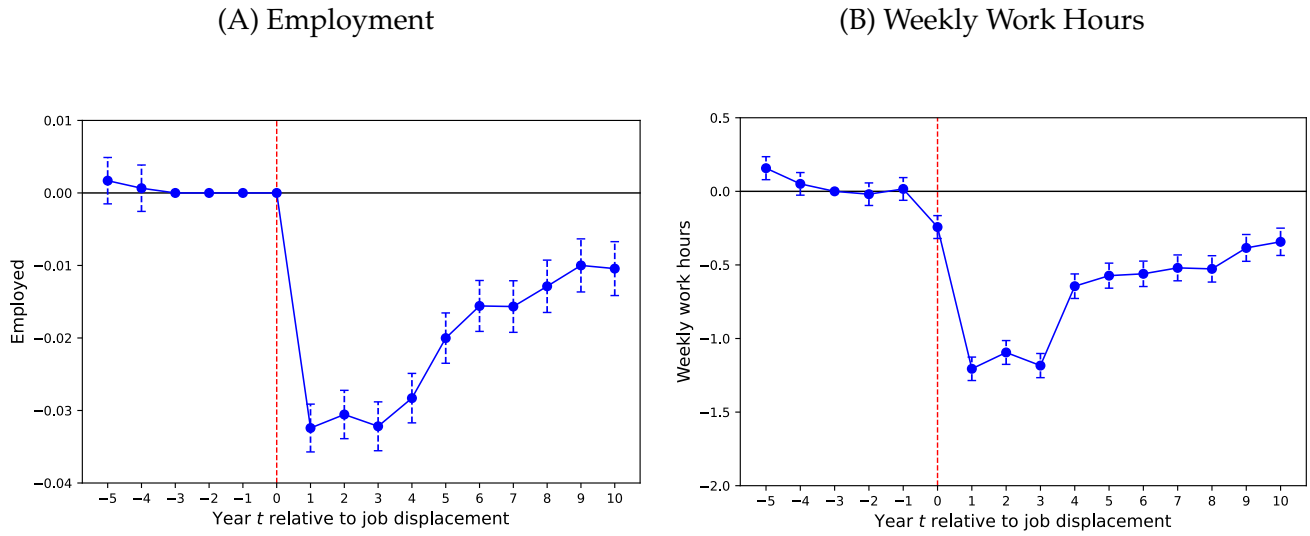
Parameter	Symbol	1D Model	2D Model	Comment
Discount rate	$r$	0.05	0.05	fixed
Risk aversion	$\eta$	1.5	1.5	fixed
Bargaining power	$\mu_f$	0.50	0.50	fixed
Separation rate	$\delta$	0.06	0.06	data estimate
Meeting rate	$\lambda$	1.00	1.00	fixed
Love shock mean	$\mu_z$	7963.97	91768.12	calibrated
Love shock standard deviation	$\sigma_z$	3034.07	44.07	calibrated
Income NAM utility parameter 1D	$\kappa_1$	0.79	–	calibrated
Income PAM utility parameter 1D	$\kappa_2$	0.34	–	calibrated
Income NAM utility parameter 2D	$\omega_1$	–	13844.73	calibrated
Unobserved PAM utility parameter 2D	$\omega_2$	–	7724811.39	calibrated
Correlation Income/Unobserved dimension	$\rho$	–	0.71	calibrated

*Notes:* This table reports the calibrated parameter values used in the quantitative versions of our framework in the 1D and the 2D version, see Section 6.3.



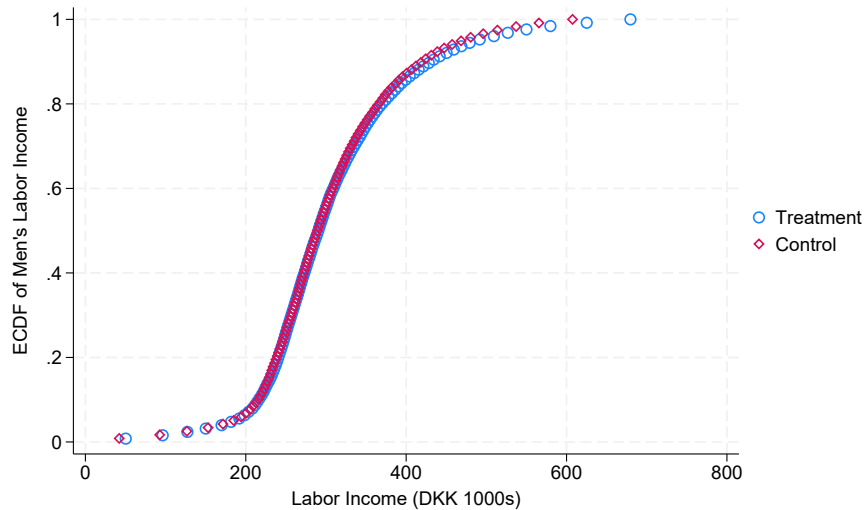
## C Additional Figures

Figure C.1: Labor Market Effects of Job Displacement



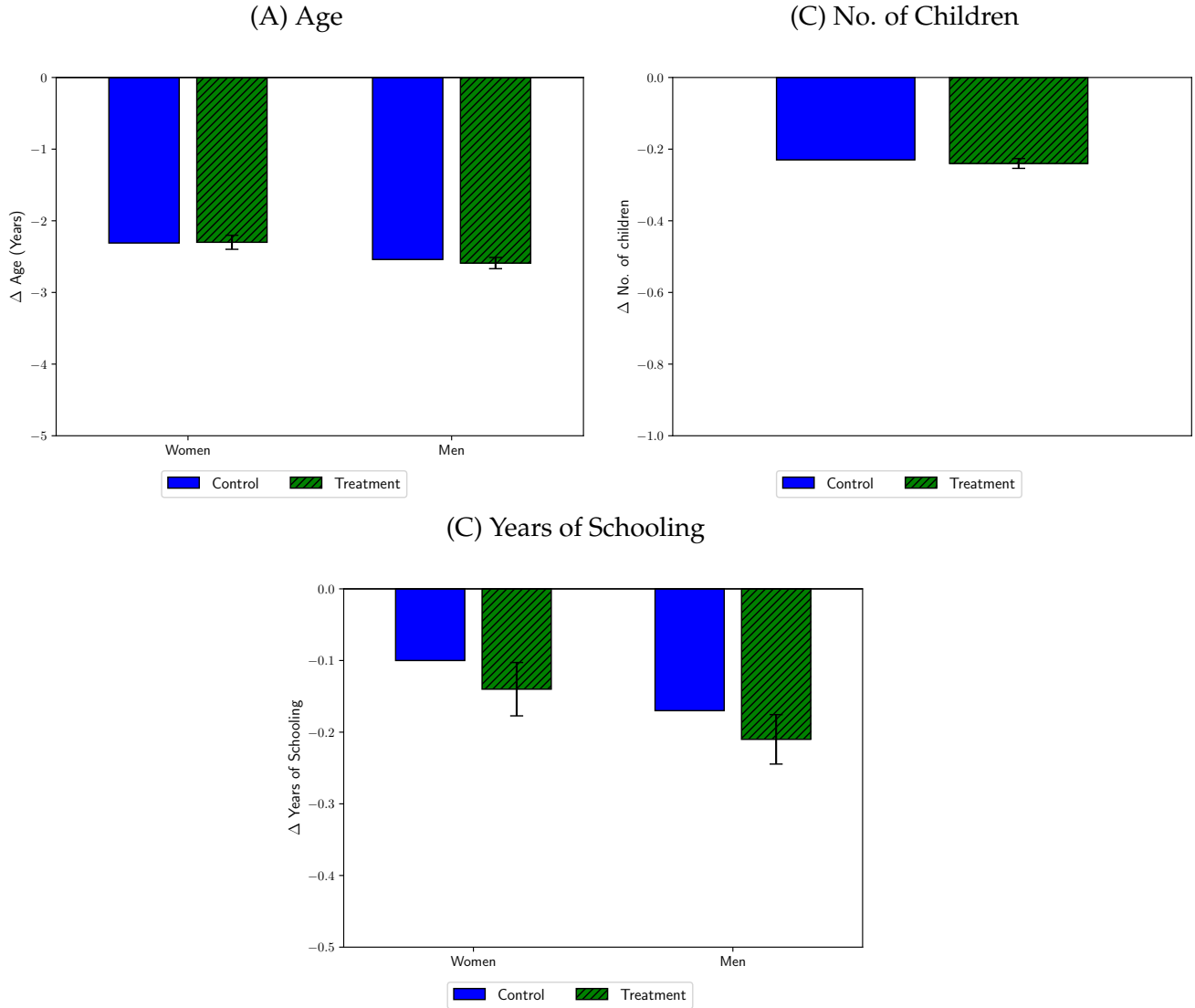
*Notes:* The figure shows the impact of job displacement on employment (Panel A) and weekly work hours (Panel B), and the associated 95% confidence intervals. The estimates correspond to estimates of  $\phi_\tau$  from equation (7). All estimates are based on a sample of men who were displaced as part of an establishment closure between 1980-2007, and the same number of control individuals selected by coarsened exact matching. The specific sample selection criteria and matched sampling algorithm are described in subsection 3.3.

Figure C.2: Which Couples Break Up? - Empirical CDFs, Men's Labor Income



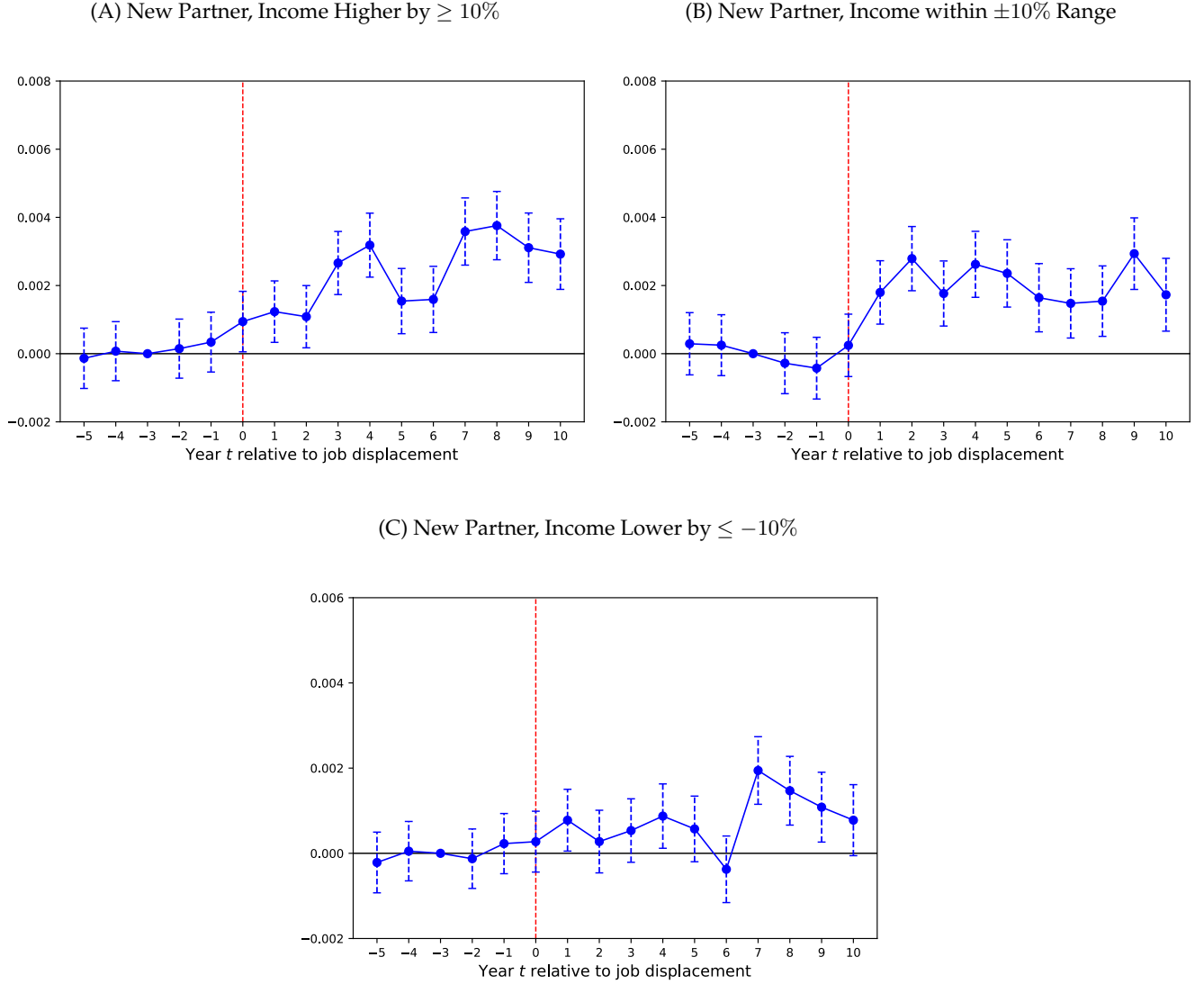
*Notes:* The figure shows the effect of job displacement on the composition of women and men who experience a breakup (in terms of their labor income distribution). The plotted empirical cdfs are computed based on pre-displacement labor income, in  $t \in \{-5, \dots, -3\}$ , of men and women who experience a break up after the male partner's actual or placebo displacement, i.e., between  $t = 0$  and  $t = 10$ . Each dot in the plot represents an average across 100 individuals (this aggregation step is necessary to ensure compliance with Statistics Denmark's data confidentiality policy). The underlying sample is our sample of men who were displaced as part of an establishment closure between 1980-2007, the same number of control individuals selected by coarsened exact matching. The specific sample selection criteria and matched sampling algorithm are described in subsection 3.3.

Figure C.3: Which Couples Break Up? - Age and No. of Children



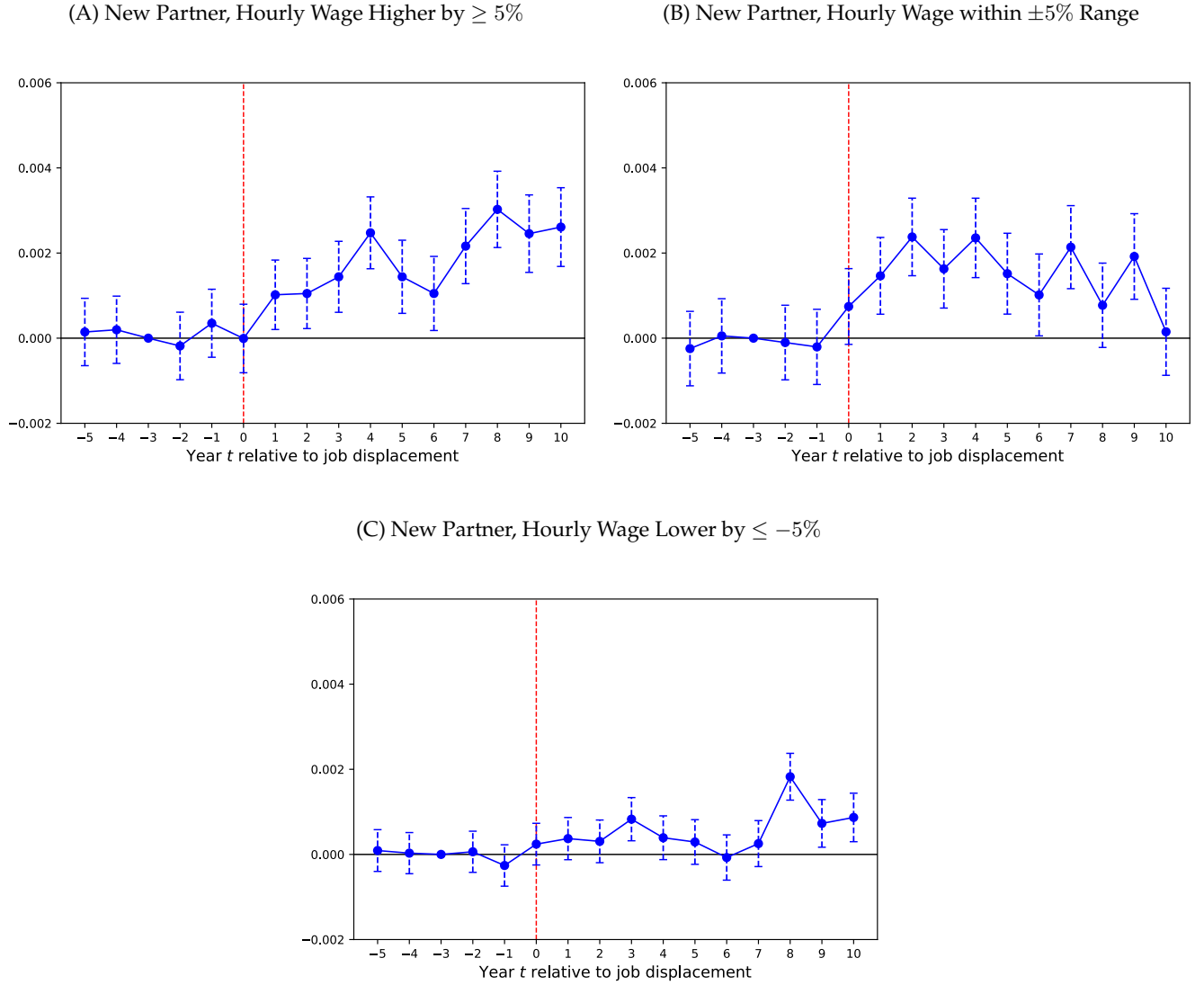
*Notes:* The figure shows the effect of job displacement on the composition of women and men (in terms of their age and no. number of children) who experience a breakup. Each plotted bar shows the average pre-displacement value (for age in Panel A and for no. of children in Panel B) in  $t \in \{-5, \dots, -3\}$ , of men and women who experience a break up after the male partner's actual or placebo displacement, i.e., between  $t = 0$  and  $t = 10$ . All values are normalized by the respective sample average. The underlying sample is our sample of men who were displaced as part of an establishment closure between 1980-2007, and the same number of control individuals selected by coarsened exact matching. The specific sample selection criteria and matched sampling algorithm are described in subsection 3.3.

Figure C.4: Impact of Job Displacement on New Partners' Income



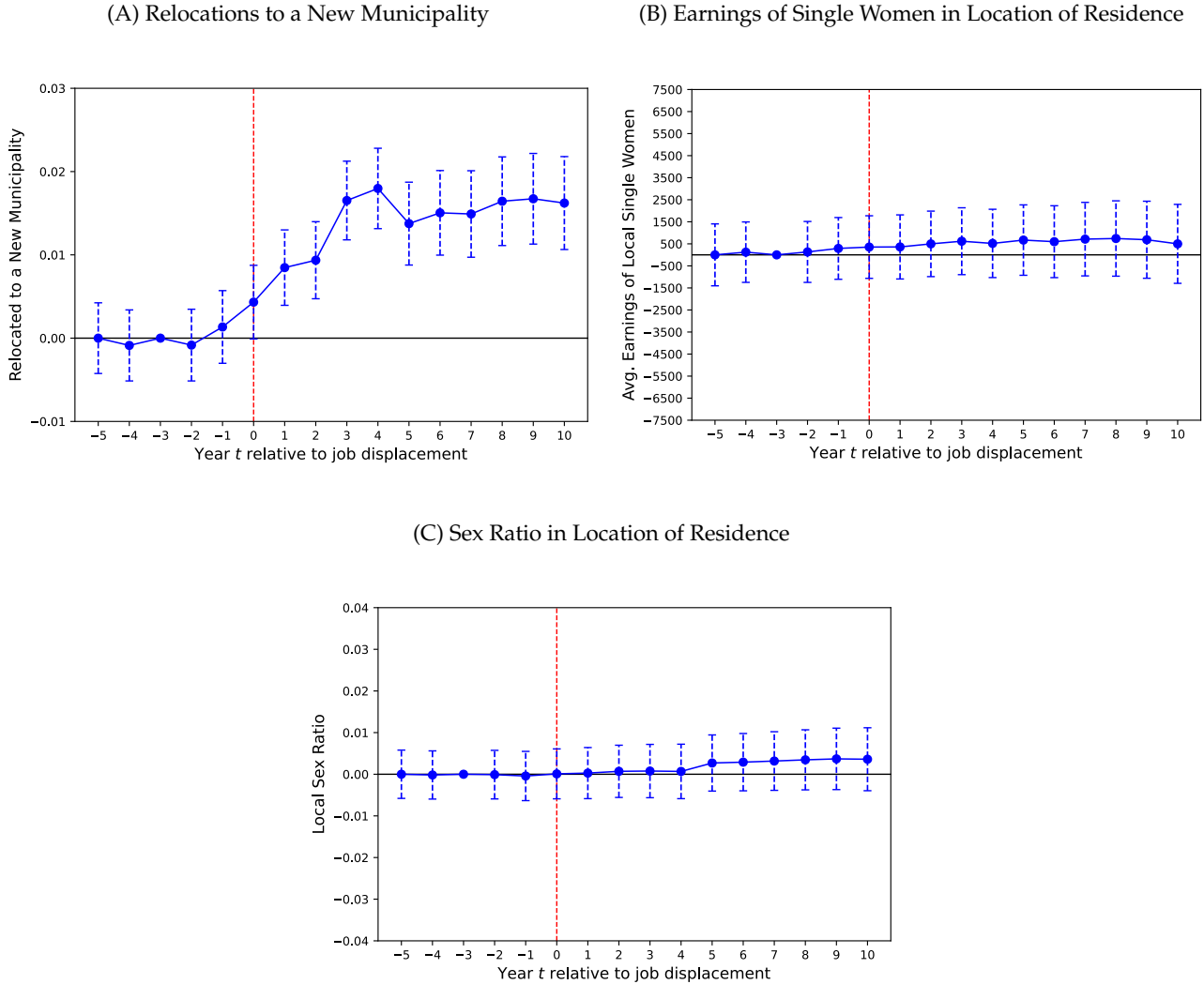
*Notes:* The displayed results show the effect of job displacement on the female type a man rematches with after a breakup, where the type is measured in terms of annual labor income. Panel A shows the impact of job displacement on the probability of matching with a new partner (who is distinct from the pre-displacement partner) who outearns the pre-displacement partner by at least 10%. Panel B shows the impact of job displacement on the probability of matching with a new partner who earns 90% or less of the pre-displacement partner's income. Panel C shows the impact of job displacement on the probability of matching with a new partner who earns within a  $\pm 10\%$  range of the pre-displacement partner's income. The estimates correspond to estimates of  $\phi_\tau$  in equation (7). The dashed vertical lines are 95% confidence intervals. All estimates are based on a sample of men who experienced an establishment closure between 1980-2007, and the same number of control individuals selected by exact matching. The sample selection criteria and matching algorithm are described in subsection 3.3.

Figure C.5: Impact of Job Displacement on New Partners' Hourly Wage



*Notes:* The displayed results show the effect of job displacement on the female type a man rematches with after a breakup, where the type is measured in terms of hourly wages. Panel A shows the impact of job displacement on the probability of matching with a new partner (who is distinct from the pre-displacement partner) who outearns the pre-displacement partner by at least 5%. Panel B shows the impact of job displacement on the probability of matching with a new partner who earns 95% or less of the pre-displacement partner's income. Panel C shows the impact of job displacement on the probability of matching with a new partner who earns within a  $\pm 5\%$  range of the pre-displacement partner's hourly wage. The estimates correspond to estimates of  $\phi_\tau$  in equation (7). The dashed vertical lines are 95% confidence intervals. All estimates are based on a sample of men who experienced an establishment closure between 1980-2007, and the same number of control individuals selected by exact matching. The sample selection criteria and matching algorithm are described in subsection 3.3.

Figure C.6: Robustness Checks



*Notes:* Panel A shows the impact of job displacement on the probability of moving to a different municipality. Panel B shows the difference between single women's average annual labor income in the municipality where the treatment and control individuals reside in period  $t$ . Panel C shows sex ratio ( $\frac{\# \text{ single women}}{\# \text{ single men}}$ ) where the treatment and control individuals reside in in period  $t$ . The estimates correspond to estimates of  $\phi_r$  in equation (7). All estimates are based on a sample of men who experienced an establishment closure between 1980-2007, and the same number of control individuals selected by exact matching. The sample selection criteria and matching algorithm are described in subsection 3.3.

## D Model Appendix

### D.1 Nash Bargaining

We assume that couples split the match surplus by agreeing on transfers,  $t_f$  and  $t_m$ , via Nash-bargaining. Define the marital surplus of a man of type  $q_m$  who is matched with a woman of type  $q_f$  by

$$S_m(q_f, q_m) = V_m^1(q_f, q_m) - V_m^0(q_m) = \frac{u_m^1(q_f, q_m) + t_m - rV_m^0(q_m)}{r + \delta}, \quad (\text{D.1})$$

and the marital surplus of a woman of type  $q_f$  who is matched with a man of type  $q_m$  by

$$S_f(q_f, q_m) = V_f^1(q_f, q_m) - V_f^0(q_f) = \frac{u_f^1(q_f, q_m) + t_f - rV_f^0(q_f)}{r + \delta}. \quad (\text{D.2})$$

Under Nash-bargaining the transfers,  $t_f$  and  $t_m$ , solve:

$$\begin{aligned} \max_{t_f, t_m} \quad & S_m(q_f, q_m)^{(1-\mu_f)} S_f(q_f, q_m)^{\mu_f} \\ \text{s.t.} \quad & t_m + t_f = 0. \end{aligned}$$

Using (D.1) and (D.2), the Nash bargaining solution is:

$$(1 - \mu_f) \left( \frac{u_m^1(q_f, q_m) + t_f - rV_f^0(q_f)}{r + \delta} \right) = \mu_f \left( \frac{u_m^1(q_f, q_m) + t_m - rV_m^0(q_m)}{r + \delta} \right). \quad (\text{D.3})$$

Equation (D.3) can be solved for the transfers,  $t_m$  and  $t_f$ :

$$t_m = rV_m^0(q_m) - u_m^1(q_f, q_m) + (1 - \mu_f) (u_m^1(q_f, q_m) + u_f^1(q_f, q_m) - rV_m^0(q_m) - rV_f^0(q_f)) \quad (\text{D.4})$$

$$t_f = rV_f^0(q_f) - u_f^1(q_f, q_m) + \mu_f (u_m^1(q_f, q_m) + u_f^1(q_f, q_m) - rV_m^0(q_m) - rV_f^0(q_f)). \quad (\text{D.5})$$

Together with (D.1) and (D.2) it follows that

$$S_m(q_f, q_m) = V_m^1(q_f, q_m) - V_m^0(q_m) = (1 - \mu_f) S(q_f, q_m), \quad (\text{D.6})$$

$$S_f(q_f, q_m) = V_f^1(q_f, q_m) - V_f^0(q_f) = \mu_f S(q_f, q_m). \quad (\text{D.7})$$

### D.2 Quantitative Model Specification

This section provides a detailed description of the quantitative specification of our framework that we calibrate and use to generate simulation results in Section 6.3.

**Type spaces and distributions** Women and men are fully characterized by their types,  $q_f \in Q_f$  and  $q_m \in Q_m$ , respectively. As described in the main text in Section 2, we allow for multidimensional types:

$Q_f = Q_m = \prod_{k=1}^K [\underline{q}_k, \bar{q}_k]$ , where each dimension,  $k$ , of the Cartesian product represents a distinct attribute. In the one-dimensional version of our framework we impose  $K = 1$ , and consider  $K = 2$  for the bidimensional case.

We denote the PDFs (and CDFs) of the male and female type distributions in the population by  $l_m(q_m)$  and  $l_f(q_f)$  ( $L_m(q_m)$  and  $L_f(q_f)$ ). The masses of men and women are normalized to one,  $\int L_m(q_m) dq_m = 1$  and  $\int L_f(q_f) dq_f = 1$ . At any given point in time, each individual is either single or married. Let  $g_f(q_f)$  and  $g_m(q_m)$  ( $G_m(q_m)$  and  $G_f(q_f)$ ) denote the endogenous PDFs (CDFs) of female and male singles. The masses of singles are endogenous, and denoted by  $\mathcal{G}_m = \int g_m(q_m) dq_m$  and  $\mathcal{G}_f = \int g_f(q_f) dq_f$ . We denote the endogenous bivariate PDF of married individuals by  $c(q_m, q_f)$ , and the mass of married couples by  $\mathcal{C} = \iint c(q_m, q_f) dq_m dq_f$ . These definitions imply that  $l_m(q_m) = \int c(q_m, q_f) dq_f + g_m(q_m)$  and  $l_f(q_f) = \int c(q_m, q_f) dq_m + g_f(q_f)$ .

**Matching technology** As described in the main text in Section 2, we assume a quadratic matching function  $\Lambda(\mathcal{G}_m, \mathcal{G}_f) = \lambda \mathcal{G}_m \mathcal{G}_f$  (see also [Mortensen, 2011](#)). The meeting rates for women and men thus equal  $\lambda_f = \frac{\Lambda(\mathcal{G}_m, \mathcal{G}_f)}{\mathcal{G}_f} = \lambda \mathcal{G}_m$  and  $\lambda_m = \frac{\Lambda(\mathcal{G}_m, \mathcal{G}_f)}{\mathcal{G}_m} = \lambda \mathcal{G}_f$ .

**Matching probabilities** As described in the main text in Section 6.3, we assume that model agents experience a match-specific shock,  $z$ , which is experienced by both partners and fixed for the duration of the match. We denote flow utilities net of the match-specific shock by  $\tilde{u}_g^1(q_f, q_m)$ , i.e.,  $u_g^1(q_f, q_m) = \tilde{u}_g^1(q_f, q_m) + z$  for  $g \in \{f, m\}$ . Under these assumptions, the probability that a man of type  $q_m$  and a woman of type  $q_f$  is given by  $\alpha(q_m, q_f) = 1 - F_z\left(-\frac{S(q_f, q_m)}{2}\right)$ , where  $F_z$  denotes the CDF of the match specific shock,  $z \sim N(\mu_z, \sigma_z)$ .

**Equilibrium Characterization and Solution** We derive four equations that characterize a steady state equilibrium in the described setup. We start from the steady-state-condition, which requires that match creation equals match destruction for any given combination of men's and women's types,  $q_f$  and  $q_m$ :

$$\delta c(q_m, q_f) = g_m(q_m) \lambda_m \frac{g_f(q_f)}{\mathcal{G}_f} \alpha(q_m, q_f) = \lambda g_m(q_m) g_f(q_f) \alpha(q_m, q_f), \quad \forall (q_m, q_f). \quad (\text{D.8})$$

Integrating (D.8) over women's type,  $q_f$ , yields the steady state flow condition for men of type  $q_m$ :

$$\delta \int c(q_m, q_f) dq_f = \lambda g_m(q_m) \int g_f(q_f) \alpha(q_m, q_f) dq_f. \quad (\text{D.9})$$

Substituting  $l_m(q_m) - g_m(q_m) = \int c(q_m, q_f) dq_f$  yields:

$$\delta (l_m(q_m) - g_m(q_m)) = \lambda g_m(q_m) \int g_f(q_f) \alpha(q_m, q_f) dq_f, \quad (\text{D.10})$$



which can be solved for  $g_m(q_m)$ :

$$g_m(q_m) = \frac{\delta l_m(q_m)}{\delta + \lambda \int g_f(q_f) \alpha(q_m, q_f) dq_f}. \quad (\text{D.11})$$

Similarly, for women of type  $q_f$ :

$$g_f(q_f) = \frac{\delta l_f(q_f)}{\delta + \lambda \int g_m(q_m) \alpha(q_m, q_f) dq_m}. \quad (\text{D.12})$$

Equations (D.11) and (D.12) jointly determine the equilibrium distributions of single women and men.

Next, we use the value of being single, given by equation (2) together with (D.6) to obtain the following extended option-value equation for single men (the option-value for single women is derived by analogous steps):

$$rV_m^0(q_m) = u_m^0(q_m) + \lambda_m \iint \max\{S_m(q_f, q_m), 0\} dF_z(z) \frac{g_f(q_f)}{\mathcal{G}_f} dq_f, \quad (\text{D.13})$$

where  $S_m(q_f, q_m) = V^1(q_f, q_m) - V^0(q_m)$  and the integral captures the option value of meeting single women, sampled from  $\frac{g_f(q_f)}{\mathcal{G}_f}$ , and drawing a match specific shock from  $F_z$ .

Using (D.13) together with (3) yields

$$rV_m^1(q_f, q_m) = \tilde{u}_m^1(q_f, q_m) + z + t_m + \delta(V_m^0(q_m) - V_m^1(q_f, q_m)), \quad (\text{D.14})$$

implying for  $S_m(q_f, q_m)$ :

$$S_m(q_f, q_m) = \frac{\tilde{u}_m^1(q_f, q_m) + z + t_m - rV_m^0(q_m)}{r + \delta}. \quad (\text{D.15})$$

Next, we use  $\lambda = \frac{\lambda_m}{\mathcal{G}_f}$  and the updated definition of male surplus  $S_m$  in (D.15) to substitute the match-specific shock  $z$  and the transfer  $t_m$  into the value of being a single man of type  $q_m$ :

$$rV_m^0(q_m) = u_m^0(q_m) + \frac{\lambda}{r + \delta} \iint \max\{\tilde{u}_m^1(q_f, q_m) + z + t_m - rV_m^0(q_m), 0\} dF_z(z) g_f(q_f) dq_f, \quad (\text{D.16})$$

where the transfers,  $t_m$ , are given by

$$\begin{aligned} t_m &= rV_m^0(q_m) - \tilde{u}_m^1(q_f, q_m) + (1 - \mu_f) (\tilde{u}_m^1(q_f, q_m) + \tilde{u}_f^1(q_f, q_m) - rV_m^0(q_m) - rV_f^0(q_f)) \\ &\quad - (2\mu_f - 1) z. \end{aligned} \quad (\text{D.17})$$

Using (D.17) together with (D.16) yields:

$$rV_m^0(q_m) = u_m^0(q_m) \quad (\text{D.18})$$

$$\begin{aligned}
& + \frac{\lambda(1 - \mu_f)}{r + \delta} \iint \max\{2z + \tilde{u}_m^1(q_f, q_m) + \tilde{u}_f^1(q_f, q_m) \\
& - rV_m^0(q_m) - rV_f^0(q_f), 0\} dF_z(z) g_f(q_f) dq_f,
\end{aligned}$$

By analogous steps we obtain for the value of being a single woman of type  $q_f$ :

$$\begin{aligned}
rV_f^0(q_f) &= u_f^0(q_f) \\
& + \frac{\lambda\mu_f}{r + \delta} \iint \max\{2z + \tilde{u}_m^1(q_f, q_m) + \tilde{u}_f^1(q_f, q_m) \\
& - rV_m^0(q_m) - rV_f^0(q_f), 0\} dF_z(z) g_m(q_m) dq_m.
\end{aligned} \tag{D.19}$$

In summary, the equilibrium is characterized by equations (D.11), (D.12), (D.18), and (D.19). We use these equations to solve our framework numerically.

**Numerical Solution** To numerically solve the 1D as well as the 2D specification of our framework, we discretize the type spaces in the income dimension (1D and 2D model) and for the unobserved characteristic (2D model only). For the income dimension, we estimate unconditional (on marital status) income distributions for men and women based on observed annual labor incomes in our estimation sample (see Section 3). Specifically, we discretize the empirical distributions by measuring the density at 50 equally-spaced income grid points.<sup>57</sup> For the unobserved characteristic in the 2D model, we set up 10 grid points with values ranging from 1 to 10 and construct distributions of male and female types across grid points using a copula, given a mean, a standard deviation, and the correlation between individual level characteristics in the two dimensions, which we denote  $\rho$ . We calibrate  $\rho$  by targeting the empirical displacement effect. We set the mean of the male and female type distributions in the unobserved dimension to 5.5 (the mid-point between 1 and 10) and the standard deviation to 1.

---

<sup>57</sup>We estimate the income density at each gridpoint using kernel density estimation. The highest income grid point is the 99th percentile of the male income distribution. The lowest income gridpoint is a small positive amount that we derive from the Danish social security system.