Job Displacement, Remarriage, and Marital Sorting*

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Abstract

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 quantitative importance of our findings by simulating how patterns of marital sorting either amplify or dampen the transmission of individual-level inequality to between-household inequality.

Keywords: Marriage Market, Sorting, Search and Matching, Multidimensional Heterogeneity

JEL classification: D1, J12, C78, D83, J31

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1 Introduction

Who marries whom plays a central role in shaping inequality. This hypothesis, inspired by Becker (1973), has motivated a large literature that studies matching patterns in the marriage market, both empirically and theoretically (Fernández and Rogerson, 2001; Greenwood, Guner, Kocharkov, and Santos, 2015; Eika, Mogstad, and Zafar, 2019; Almar, Friedrich, Reynoso, Schulz, and Vejlin, 2025a). A well-established empirical finding in this literature is that spouses' attributes, such as income (Chiappori, Fiorio, Galichon, and Verzillo, 2022), education (Schwartz and Mare, 2005), and wealth (Charles, Hurst, and Killewald, 2012; Fagereng, Guiso, and Pistaferri, 2022), tend to be positively associated across couples. However, the underlying mechanisms that give rise to these matching patterns remain imperfectly understood. Consider the case of income: do the observed cross-sectional associations in spouses' incomes reflect sorting on income? Are these patterns informative about whether incomes are complements or substitutes in the marriage market? Or do they arise through other channels, for example, because individuals sort on other, potentially unobserved traits that are correlated with income?

We offer novel evidence on how the association between spousal attributes arises through marriage and divorce decisions. Our analysis exploits quasi-experimental variation from establishment closures in Danish register data, leveraging job displacement as an exogenous shock to a person's marriage market value. We interpret our empirical findings through the lens of a search and matching model of the marriage market in which job displacement endogenously influences marriage and divorce decisions. Our empirical findings show that job displacement increases separation rates—particularly among men matched with low-income partners—and raises the likelihood of rematching with higher-income partners. This pattern suggests a negative relationship between spousal incomes: displaced men lose income and subsequently rematch with higher-income women. To scrutinize this pattern and assess how it can be reconciled with the positive cross-sectional relationship between spouses' incomes, we draw on a search and matching framework of marriage and divorce. We build on Shimer and Smith (2000) who embed Becker's (1973) model of sorting into an equilibrium search and matching framework. Their framework has served as the basis for a burgeoning literature that examines marriage market sorting as the outcome of endogenous and recurring marriage and divorce decisions (Jacquemet and Robin, 2013; Greenwood, Guner, Kocharkov, and Santos, 2016; Goussé, Jacquemet, and Robin, 2017; Holzner and Schulz, 2023). The model is general, nesting a wide range of models of intra-period household consumption, labor supply, and time allocation. We use the model to derive predictions about the treatment and selection effects that shape our empirical results, treating job displacement as an exogenous reduction in agent type that affects marital surplus. By comparing the model predictions to our empirical findings, we assess which model assumptions and mechanisms are consistent with the observed behavior following job displacement.

Our empirical analysis compares over 72,000 displaced male workers to a non-displaced control group. We follow both groups over time and compare their transitions into and out of marriages and cohabiting relationships. Our research design relies on establishment closures as a source of exogenous variation, thereby circumventing the endogeneity of individual job loss and voluntary quits. We document persistent earnings losses following displacement and show that marriage market outcomes—such as separation rates, the characteristics of couples who separate, rematching rates, and the composition of new matches—differ significantly between the treatment and the control group. We find that displaced men are (i) more likely to experience a breakup, (ii) particularly more likely to do so when matched with a low-earning partner, (iii) more likely to remain single after a breakup, and (iv) more likely to transition from a low-earning to a higher-earning partner when rematching, compared to the non-displaced control group. Importantly, finding (iv) is not driven by labor supply choices but by men matching with new partners who earn higher hourly wages. Note that findings (ii)–(iv) reflect a combination of treatment and selection effects. Our structural model is well suited to analyze these findings because it features endogenous selection into divorce and remarriage in response to job displacement. We find no notable differences between treatment and control group with respect to partners' age, education, or number of children. We perform robustness checks to rule out that our findings are driven by selective migration of displaced men to municipalities with higher-earning women or where men are relatively scarce. While our main analysis focuses on displaced men, we document qualitatively similar separation and rematching patterns for displaced women. These effects are estimated less precisely, and displaced women's earnings losses are smaller and less persistent.

Using our structural framework, we demonstrate that these empirical findings pose a challenge for standard models of marital sorting: we show formally that our findings (in particular (ii) and (iv)) suggest negative assortative matching (NAM), while the positive cross-sectional correlation of spousal incomes points to positive assortative matching (PAM).[1] It is challenging to reconcile both empirical facts within conventional models of marital sorting, which generate either PAM or NAM. As shown by Becker (1973), positive sorting can be explained by complementarities in the marital match value.[2] Building on this idea, the literature has proposed a variety of mechanisms that generate such complementarities—such as complementarities in home production hours or education homophily—to match the observed positive correlation in spousal income and education.[3] By contrast, substitutability in home production hours (leading to household specialization) or risk sharing lead to substitutability between spouses' characteristics and would give rise to negative cross-sectional correlations in spousal income.[4] All of these mechanisms have in common

[1]Our proof accounts for both selection and treatment effects of job displacement and shows that, under both PAM and NAM, the selection effect points in the same direction as the treatment effect.

[2]Intuitively, similar individuals match if spouses' characteristics are complements, whereas dissimilar individuals match if characteristics are substitutes. Formally, positive (negative) sorting arises if the match value from marriage is supermodular (submodular); see Becker (1973).

[3]For example, complementarities in home production hours (Goussé et al., 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 the consumption of market-purchased public goods Lam (1988) generate complementarities in the match value.

[4]See Becker (1973) and Becker (1981) for examples of models with substitutability in home production hours that lead to household specialization and negative sorting. Risk sharing generates substitutability in spouses' types, e.g., in Chiappori et al. (2018) and Pilossoph and Wee (2021).

that the underlying models typically assume one-dimensional heterogeneity.[5] This creates a tight link between the complementarity or substitutability of spousal traits and cross-sectional sorting patterns.[6] Our empirical results challenge this tight link: our evidence from job displacements can be rationalized by substitutability in the match value (implying NAM), yet sorting on income in the cross-section is positive.

We offer an explanation that reconciles this tension between theory and evidence by relaxing the assumption of one-dimensional heterogeneity maintained in Shimer and Smith (2000) and related models. Specifically, we develop a multidimensional extension of the framework and formally show that the extended model can jointly explain our empirical findings (i)–(iv) and the positive cross-sectional correlation between matched spouses' incomes. To this end, we define multidimensional notions of PAM and NAM, where sorting is defined dimension by dimension, allowing PAM to arise in one dimension, while NAM arises in another.[7] Our proposed specification features negative sorting on income and positive sorting on other characteristics, including unobserved traits.[8] Intuitively, if job displacement affects only certain dimensions of an agent's type (such as earnings potential or health), then sorting along those dimensions will shape rematching patterns in response to displacement. In contrast, the cross-sectional correlation between partners' incomes may be governed by sorting on other characteristics that are unaffected by displacement (such as age or height) and that are correlated with income. Compared to one-dimensional models, the link between complementarities in the match value and sorting thus becomes more nuanced: even if spouses' incomes are substitutes, such that sorting on income itself is negative, a positive correlation between spouses' incomes may arise due to positive sorting on other characteristics that correlate with income.

We discuss several further implications of our findings for how marriage market sorting is modeled and interpreted. First, our multidimensional framework offers a unifying perspective: mechanisms that generate negative sorting on income (e.g., gains from household specialization) and those that generate positive cross-sectional correlations in spouses' incomes (e.g., homophily on education or other traits) do not necessarily counteract each other but may coexist and shape sorting along different dimensions. This perspective reconciles Becker's (1973) prediction of negative sorting on income with the mechanisms invoked in the literature to account for the observed positive correlation in spouses' incomes, such as education homophily (e.g., Chiappori et al. 2009, 2018) or sorting on home productivities (e.g., Goussé et al. 2017; Chiappori et al. 2017b; Calvo et al. 2024). In the multidimensional framework, sorting on income—conditional on all other characteristics—is negative, consistent with Becker's prediction, whereas sorting in other dimensions (e.g., due to education homophily) may generate a positive unconditional correlation in spouses' incomes. A related implication is that unconditional empirical correlations in

[5] While many models allow for matching on multiple characteristics, they typically assume that these characteristics are perfectly dependent (e.g., income is fully determined by education) or can be summarized by a scalar index, effectively reducing matching to one-dimensional sorting.

[6] This applies to both models with search frictions and frictionless matching (see, e.g., Choo and Siow 2006; Chiappori 2017).

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

[8] By "unobserved," we refer to traits that are observed by agents in the model but not observed in our data. In Section 6.2, we provide empirical evidence suggesting that such unobserved traits play a quantitatively important role in explaining our findings.

spousal characteristics reflect sorting across all dimensions and therefore conflate the influence of multiple underlying mechanisms. By contrast, leveraging exogenous variation in one characteristic, holding others fixed, captures the mechanisms that drive sorting along that specific dimension.

Second, our findings suggest a quantitatively important role of both observed and unobserved characteristics in shaping marital sorting. We decompose the cross-sectional correlation between matched spouses' incomes into components attributable to sorting on income, sorting on other observed characteristics (e.g., age, education), and sorting on unobserved traits. Interpreting the evidence from job displacements through our multidimensional matching framework allows us to derive a lower bound on the contribution of unobserved characteristics: at least 44% of the positive coefficient from regressing wives' income on husbands' income is attributable to sorting on unobserved traits.

Third, we illustrate the quantitative relevance of our findings by calibrating both a one-dimensional and a bidimensional version of our framework. The calibrated bidimensional model matches both the positive correlation in spouses' incomes and our new empirical evidence on rematching after job displacement. In line with our theoretical results, the one-dimensional model fails to match both patterns simultaneously. We then use both models to simulate a counterfactual rise in individual income inequality and examine how marital sorting shapes the resulting change in between-household inequality. The models yield starkly different predictions: the one-dimensional model predicts that positive sorting on income amplifies the rise in between-household inequality, while the bidimensional model predicts that marital sorting on income dampens it. These simulations show that the mechanisms underlying observed sorting patterns matter for how individual income inequality translates into household-level inequality.

Our paper is related to several strands of the literature. Our primary contribution is to the literature that studies marital sorting using equilibrium models with two-sided heterogeneity (e.g., Becker, 1973, 1981; Wong, 2003; Choo and Siow, 2006; Greenwood et al., 2016; Goussé et al., 2017; Coles and Francesconi, 2019; Pilossoph and Wee, 2023; Almar, Friedrich, Reynoso, Schulz, and Vejlin, 2025b). We contribute to this literature by providing novel empirical evidence from job displacements and assessing to what extent common modeling assumptions are consistent with the empirical patterns we document.[9] Our findings highlight the importance of multidimensional matching, which is often abstracted from by assuming that traits perfectly align or can be summarized by a single index. In particular, our findings suggest that cross-sectional sorting patterns in income arise not only from sorting on income itself but also from sorting on unobserved traits that are correlated with income, as previously suggested, e.g., by Becker (1981), Coles and Francesconi (2011), and Low (2024).[10]

[9]Our empirical analysis builds on and extends previous studies documenting that job displacement increases the risk of separation (e.g., Charles and Stephens, 2004; Eliason, 2012; Huttunen and Kellokumpu, 2016; Banzhaf, 2018). We add to their contribution by examining how job displacement affects both selection into divorce and subsequent rematching patterns. Note that both the empirical patterns we document and the model predictions we compare them to are a combination of treatment and selection effects.

[10]Becker (1981) suggests: "The positive correlation between wage rates of husbands and wives [...] may really be measuring

We thereby also contribute to a growing literature that explores multidimensional marriage market matching. While most matching models used in applied work are one-dimensional, several papers have studied multidimensional frictionless matching models (e.g., Chiappori, Oreffice, and Quintana-Domeque, 2012; Dupuy and Galichon, 2014; Adda, Pinotti, and Tura, 2024; Low, 2024). A small number of studies examine multidimensional matching in settings with search frictions (e.g., Coles and Francesconi, 2011, 2019; Cheremukhin, Restrepo-Echavarria, and Tutino, 2024). Both strands focus on match formation and abstract from divorce and remarriage. Related work in the labor market context has developed multidimensional search and matching models with recurring match formation and dissolution (e.g., Lindenlaub and Postel-Vinay, 2021, 2023). We complement these previous studies by proposing a multidimensional extension of the equilibrium search and matching model with two-sided heterogeneity introduced by Shimer and Smith (2000). Our framework adds to the literature by allowing for recurring marriage and divorce in a multidimensional matching environment. This setup allows us to examine how multidimensional sorting emerges from marriage and divorce decisions and how these decisions endogenously respond to adverse job displacement shocks. Importantly, in contrast to most previous multidimensional models, we allow unobserved characteristics to be correlated with observed ones. This feature is essential in light of our findings, which suggest that sorting on unobservables plays a central role in explaining observed patterns of sorting on income.

Finally, our paper is related to studies that use structural matching models to examine how marital sorting responds to counterfactual changes, e.g., in the wage structure (Fernández, Guner, and Knowles 2005, Greenwood et al. 2016, Shephard 2019, Calvo et al. 2024), or in policies such as 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). Relative to this literature, our findings suggest a stronger role for mechanisms such as household specialization and risk sharing, which are difficult to reconcile with positive cross-sectional income sorting in one-dimensional models. By contrast, in the multidimensional framework supported by our evidence, these mechanisms naturally align with observed cross-sectional sorting and help explain empirical rematching patterns following job displacement. Our simulations, based on calibrated one-dimensional and bidimensional versions of our framework, illustrate the quantitative relevance of the mechanisms underlying marital sorting for structural modeling and counterfactual policy analysis.

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 the quantitative implications of our findings, and Section 7 concludes.

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."

2 Conceptual Framework

This section introduces a search-and-matching model of the marriage market, which we use as a conceptual framework to study how job displacement shapes marriage market transitions. We build on the frictional extension of Becker's (1973) assignment model developed by Shimer and Smith (2000), which features two-sided heterogeneity and transferable utility. Our framework yields predictions about how job loss triggers endogenous selection into divorce and remarriage, as well as changes in women's and men's search behavior. We use these predictions to interpret our empirical findings and to assess which modeling assumptions are consistent with observed data patterns. The framework is deliberately general, placing minimal structure on functional forms and the distributions of agent types. Yet, we show that it yields testable implications under PAM and NAM, which we subsequently confront with the data.

2.1 Setup

We consider a two-sided matching environment populated by women and men, denoted by f and m, respectively. Time is continuous and discounted at rate r. Women and men are characterized by their types, $q_f \in Q_f$ and $q_m \in Q_m$. We allow for multidimensional type spaces, assuming that $Q_f = Q_m = \prod_{k=1}^{K} \left[\underline{q}_k, \overline{q}_k\right]$, where each dimension, k, of the Cartesian product represents a distinct type attribute. We clearly indicate when we consider the special case of one-dimensional matching ($K = 1$) or the more general multidimensional case ($K > 1$). Search is random. Denote by G_f and G_m the cumulative distribution functions (CDFs) of single women's and men's types, respectively.[11] At rate λ_f, a single woman meets a single man drawn from G_m. Conversely, at rate λ_m, a single man meets a single woman, drawn from G_f. Following Shimer and Smith (2000), we assume that meeting rates for men and women are proportional to the mass of singles of the opposite gender: $\lambda_f = \bar{\lambda} \int dG_m(q_m)$ and $\lambda_m = \bar{\lambda} \int dG_f(q_f)$, where $\bar{\lambda}$ is a scaling factor that governs how meeting rates depend on the mass of singles on the other side of the marriage market. Upon meeting, agents observe each other's types and jointly decide whether to form a match or continue searching.

2.2 Flow Utilities

The flow utility of a single agent of gender $g \in \{f, m\}$ and type q_g is given by $u_g^0(q_g)$, and is weakly increasing in q_g.[12] When matched, women and men receive flow utilities $u_f^1(q_f, q_m)$ and $u_m^1(q_f, q_m)$, which are weakly increasing in both own and partner's type. The flow value of a match, $f(q_f, q_m)$, is the sum of the partners' individual flow utilities,

$$f(q_f, q_m) = u_f^1(q_f, q_m) + u_m^1(q_f, q_m). \tag{1}$$

[11]Note that G_f and G_m are endogenous equilibrium objects.

[12]Throughout, model objects with superscript 0 refer to singles, whereas those with superscript 1 refer to matched agents.

We do not impose functional form assumptions on $u_g^1(q_f, q_m)$ or $u_g^0(q_g)$. The framework is therefore flexible, nesting a wide range of models of intra-period household decision-making, as these flow utilities can be interpreted as indirect utilities derived from an underlying model of household behavior. For an example of this approach, see Goussé et al. (2017) who embed a model of intra-period household time and resource allocation into the Shimer and Smith (2000) search and matching framework.

2.3 Bellman Equations, Matching, and Surplus Division

A model agent's decision problem is characterized by two Bellman equations. The value of being a single man of type q_m is given by

$$rV_m^0(q_m) = u_m^0(q_m) + \lambda_m \int \max\{V_m^1(q_f, q_m) - V_m^0(q_m), 0\} dG_f(q_f), \tag{2}$$

where $V_m^1(q_f, q_m)$ denotes the value to a type-q_m man of matching with a woman of type q_f. This equation reflects that the value of singlehood is determined by the flow utility from being single and the option value of meeting a partner. The value of a match with a woman of type q_f, from the perspective of a type-q_m man, is

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

where t_m denotes the intra-household utility transfer, which may be positive or negative.[13] δ denotes the exogenous separation rate, capturing match dissolution not triggered by job loss. In addition, we explicitly model endogenous separations that occur in response to unexpected job displacement. The mechanisms through which job loss triggers endogenous separations, and thereby gives rise to selection into divorce and remarriage, are discussed in detail in Sections 2.5 and 2.6.

Given (2) and (3), the marital surplus is defined as

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

Under transferable utility, the marital surplus can be freely redistributed between spouses. A couple therefore chooses to match upon meeting if and only if the surplus is weakly positive, $S(q_f, q_m) \geq 0$. In this case, transfers can be set so that each spouse individually benefits relative to remaining single. We close the model by assuming that the surplus is divided through Nash bargaining, which implies transfers are set so that the female partner receives a share $\mu_f S(q_f, q_m)$, and the husband receives the remainder, $(1 - \mu_f)S(q_f, q_m)$, where $\mu_f \in [0, 1]$ denotes her Nash bargaining weight (see Appendix C.1 for details).

[13]The value functions for single women and for type-q_f women matched with type-q_m men are defined analogously to (2) and (3). Transfers are restricted to be net-zero, i.e., $t_m = -t_f$.

2.4 Equilibrium and Sorting

For the one-dimensional case, $K = 1$, Shimer and Smith (2000) prove the existence of a steady-state equilibrium in which agents' decisions are optimal, that is, they solve the Bellman equations (2) and (3), and the inflow and outflow of matches balance for each agent type.[14]

Shimer and Smith (2000) further characterize equilibrium sorting by generalizing Becker (1973)'s concepts of PAM and NAM to a frictional matching environment.[15] Denote by $\mathcal{M}(q_m)$ the matching set for a man of type q_m, that is, the set of female types with whom he matches upon meeting. Shimer and Smith (2000) show that matching sets take the form of closed intervals, $[a(q_m), b(q_m)]$, in equilibrium. Under PAM, the interval bounds $a(q_m)$ and $b(q_m)$ are weakly increasing in q_m, while under NAM, they are weakly decreasing.[16] These relationships allow us to analyze how an unexpected shock to an agent's type (due to job loss) affects their matching set and, in turn, which couples dissolve and which new couples form in response.

Moreover, using these relationships, it can be shown that PAM and NAM imply the following cross-sectional correlations:

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

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

(5) and (6) form the basis for interpreting the widely documented positive correlation between spouses' earnings and between their education levels as evidence in favor of PAM and against NAM (under the assumption that agent types map into income and education).

2.5 The Impact of Job Loss on Marriage Market Dynamics

We now connect our conceptual framework to the empirical setting by modeling job displacement as a permanent, unexpected reduction in an agent's type.[17] We further assume that an agent's type maps into their earnings potential, which we measure empirically using labor income and hourly wages.[18] 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 $d > 0$.

[14] Lauermann, Nöldeke, and Tröger (2020) provide a more general existence proof and argue that it extends to multidimensional settings.

[15] We state the formal definition by Shimer and Smith (2000) in Appendix A.

[16] See Shimer and Smith (2000), Propositions 2 and 3.

[17] Since job displacement is unexpected, it does not occur at a positive rate in the Bellman equations.

[18] While labor income is affected by endogenous labor supply choices, this is less of a concern for hourly wages. Throughout, we report results for both labor income and hourly wages, and all findings hold for each measure. We also show that our results based on labor income are not driven by changes in work hours (see Section 4.4 and 4.6). Formally, we assume strictly increasing mappings from agents' types, q_f and q_m, to hourly wages and labor income. Note that this assumption does not rule out that agent types also influence other characteristics (such as health). Finally, the assumption that type reductions are permanent is consistent with extensive empirical evidence documenting long-run wage losses following job displacement (e.g., Jacobson, LaLonde, and Sullivan, 1993; Sullivan and von Wachter, 2009).

Given this formal definition of job loss, our framework allows us to derive predictions about how job displacement affects the endogenous selection of agents into divorce and remarriage, and how their search behavior changes in response. Job displacement triggers an endogenous divorce for any couple (q_f, q_m) whose marital surplus becomes negative after displacement, $S(q_f, q_m - d) < 0$. Following divorce, the displaced man remarries if he meets a single woman of type q_f, such that $S(q_f, q_m - d) \geq 0$. We use our framework to derive predictions about which couple types (q_f, q_m) separate endogenously following male job displacement, and which new matches subsequently form. We then compare these predictions to selection and treatment effects that we estimate empirically. The goal is to assess which model assumptions are consistent with the observed empirical patterns (see Section 3).

To connect the model predictions with our empirical analysis, consider two groups of men, a treatment group and a control group, observed at two points in time, t_0 and $\tau > t_0$. Assume that all men in both groups are matched with a female partner in period t_0. Men in the treatment group are displaced at t_0, while those in the control group are not displaced between t_0 and τ. It follows that $q_m(\tau) = q_m(t_0) - d$ for treated men and $q_m(\tau) = q_m(t_0)$ for control men. Throughout, we assume that the treatment group is small (i.e., of measure zero), so that job displacements affect the displaced agents but do not induce a transition to a different steady-state equilibrium.

We denote by D a treatment indicator equal to 1 for the (displaced) treatment group and 0 for the (non-displaced) control group. The CDFs of men's types in the treatment and control group are denoted by $F(q_m \mid D = 1)$ and $F(q_m \mid D = 0)$, respectively. We further define D_B as an indicator for whether a man separates from his t_0-partner between t_0 and τ, and D_R as an indicator for whether he rematches with a new partner over the same interval.

We derive predictions regarding the following treatment and selection effects of job displacement.

1. Treatment effect on breakup risk:

$$\gamma_B = P\left(D_B = 1 | D = 1\right) - P\left(D_B = 1 | D = 0\right),$$

which captures the effect of job displacement on the probability that a man separates from his initial partner.

2. Selection effect on the types of men and women who break up:

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

which capture how job displacement affects the composition of couples who separate (e.g., whether displacement disproportionately induces breakups among high- or low-type individuals).

3. Combined selection and treatment effect on the probability of remaining single after a breakup:

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

which reflects both changes in the composition of singles and in a given man's likelihood of rematching, as a result of job displacement.

4. Combined selection and treatment effect on rematching patterns:

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

which reflects changes in the composition of singles who rematch, as well as in the average type of partner a given man is expected to match with following job displacement.

The following result shows that our framework yields testable predictions about the sign of the described effects under PAM and NAM.[19] Note that the predictions regarding effects 3. and 4. reflect a combination of selection and treatment effects. The proof of Proposition 1 derives the sign of both the selection and the treatment margin and shows that, under both PAM and NAM, the selection effect points in the same direction as the treatment effect. In Section 4.5, we compare these model predictions to empirical estimates that likewise capture both treatment and selection effects.

Proposition 1. *Consider the one-dimensional case, $K = 1$, of the described matching environment in steady-state equilibrium.*

Under either PAM or NAM:

1. *Job displacement increases the breakup risk: $\gamma_B \geq 0$.*
2. *Job displacement may increase or decrease the probability of remaining single after a break up: $\gamma_{R=0|B}$ 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: $\gamma_{\Delta q_f|R} \leq \overline{\gamma}_{\Delta q_f|R}$. The upper bound is given by*

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

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 non-displaced men separate: $\gamma_{q_f|B} \geq 0$.*

[19] For proofs and derivations, see Appendix A.

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 non-displaced men separate:* $\gamma_{q_f|B} \leq 0$.

Relationships (*3.-a*) and (*5.-a*) show that under PAM, displaced men are more likely to separate when matched with a high-type female partner and, on average, rematch with lower-type women relative to the non-displaced control group. By contrast, under NAM, relationships (*3.-b*) and (*5.-b*) imply that displaced men are more likely to separate from low-type partners and, on average, rematch with higher-type women. Moreover, relationships (*4.-a*) and (*4.-b*) show that the magnitude of downward or upward rematching is bounded away from zero. The bounds are determined by the slope of $\mathbb{E}[q_f|q_m]$ in q_m, yielding additional testable implications.

Finally, note that the predictions derived in Proposition 1 rely solely on assumptions about equilibrium sorting and hold for any flow utilities, $u_g^1(q_f, q_m)$ and $u_g^0(q_g)$, as long as they imply PAM or NAM. As a result, empirical evidence that contradicts prediction (*3.-a*), (*4.-a*), or (*5.-a*) rules out any specification of our framework that implies PAM. This includes both any flow utility functions that generate PAM but also any underlying models of household decision-making from which such flow utilities may be derived.[20] Similarly, evidence that rejects predictions (*3.-b*), (*4.-b*), or (*5.-b*) rules out any specification that implies NAM.

2.6 Mechanisms: Endogenous Separations and Rematching

To provide the intuition behind Proposition 1, we now describe the underlying model mechanisms. When a matched male agent loses his job, his type q_m decreases to $q_m - d$. This reduces both his and his female partner's flow utility from marriage, $u_m^1(q_f, q_m)$ and $u_f^1(q_f, q_m)$. The female partner's outside option remains unchanged (as it does not depend on q_m), whereas the male partner's outside option, $V_m^0(q_m)$, declines.[21] As a result, the difference $u_f^1(q_f, q_m) - rV_f^0(q_f)$ shrinks, lowering the female partner's marital surplus share for a given transfer t_f.[22] For the male partner, both his flow utility from marriage and his

[20]As noted above, the flow utilities, $u_m^1(q_f, q_m)$ and $u_g^0(q_g)$, can be interpreted as indirect utilities from an underlying model of intra-period household decision-making. For examples of such models, see, e.g., Goussé et al. (2017) and Chiappori (2017).
[21]$V_m^0(q_m)$ is weakly increasing in q_m, by Lemma 1 in Shimer and Smith (2000).
[22]This follows directly from equation D.2.

outside option decrease. Depending on which effect dominates, the difference $u_m^1(q_f, q_m) - rV_m^0(q_m)$, and thus the male's marital surplus share, may increase or decrease. If the couple stays together, transfers adjust to compensate the partner who experienced the larger decline in $u_g^1(q_f, q_m) - rV_g^0(q_g)$.[23] The couple breaks up if the overall marital surplus after job loss is negative, or equivalently if[24]

$$u_f^1(q_f, q_m - d) + u_m^1(q_f, q_m - d) - rV_f^0(q_f) - rV_m^0(q_m - d) < 0.$$

In this case, there is no level of transfers such that both partners prefer staying together over breaking up. This provides the intuition behind part *1.* of Proposition 1.

Which types of couples break up following the male partner's job loss can be understood intuitively by considering the sign of the cross-partial derivatives $\frac{\partial^2 u_g^1}{\partial q_m \partial q_f}$ (for $g \in \{f, m\}$).[25] If the cross-partial derivatives are positive, the decline in each partner's flow utility following the male partner's job loss is greater when the female partner has a higher type:

$$u_g^1(q_f, q_m) - u_g^1(q_f, q_m - d) < u_g^1(q_f', q_m) - u_g^1(q_f', q_m - d) \quad \text{for } \; q_f < q_f' \; g \in \{f, m\}. \tag{7}$$

This larger loss in flow utility makes couples with high-type female partners relatively more likely to break up following the male partner's job loss.[26] Conversely, if the cross-partial derivatives are negative, the decline in the male partner's flow utility is larger when the female partner has a lower type, making couples with low-type women more likely to break up. This provides the intuition underlying parts *5.-a* and *5.-b* of Proposition 1.

The remarriage prospects of men who lose their jobs are also shaped by the sign of the cross-partial derivatives $\frac{\partial^2 u_g^1}{\partial q_m \partial q_f}$. Suppose a couple (q_f, q_m) breaks up following the male partner's job loss, implying that their marital surplus after the shock is negative, $S(q_f, q_m - d) < 0$. We now outline the intuition for how the sign of the cross-partial derivatives affects the feasibility of rematching with a woman of higher or

[23]This logic is closely related to limited commitment models, where bargaining power adjusts when individual participation constraints are violated (e.g., Mazzocco 2007; Voena 2015; Foerster 2024; Verriest 2024). Our model differs in two key respects: first, since we assume transferable utility, surplus redistribution in response to changes in outside options occurs entirely through adjustments in transfers rather than changes in bargaining power. Second, we allow transfers to respond to job loss shocks, regardless of whether participation constraints bind (essentially assuming no commitment). Note, however, that while transfer levels would differ, our model's predictions regarding separations and rematching remain unchanged if transfers were adjusted only when one partner's participation constraint is violated.

[24]In limited commitment models of marriage and divorce, it is common to interpret a partner whose participation constraint is violated as initiating the divorce (this may be either partner or both simultaneously). We can adopt a similar interpretation and define a partner for whom $u_g^1(q_f, q_m) < rV_g^0(q_g)$ as initiating the divorce. After a male job loss, each partner's marriage flow utility declines and may fall below their respective outside options. At the same time, the male partner's outside option is reduced, making it less likely that his participation constraint gets violated. All things considered, after male job loss, either partner may initiate divorce. Which partner initiates it depends on whose participation constraint was close to binding initially, on the relative magnitude of the decline in marital flow utility, and on the male outside option.

[25]Positive cross-partial derivatives, $\frac{\partial^2 u_g^1}{\partial q_m \partial q_f} > 0$ imply $\frac{\partial^2 f}{\partial q_m \partial q_f} > 0$, which is part of the sufficient conditions for positive assortative matching established by Shimer and Smith (2000). Similarly, negative cross-partial derivatives imply $\frac{\partial^2 f}{\partial q_m \partial q_f} < 0$, which is part of Shimer and Smith (2000)'s sufficient conditions for negative assortative matching.

[26]Note that the change in the male partner's outside option due to job loss, $V_m^0(q_m - d) - V_m^0(q_m)$, is independent of the female partner's type, and therefore does not contribute to heterogeneity in break-up risk across q_f-types.

lower type than his previous partner. Suppose that the cross-partial derivatives are positive. In this case, job loss reduces a man's utility gain from matching with a higher-type woman:

$$u_m^1(q_f', q_m - d) - u_m^1(q_f, q_m - d) < u_m^1(q_f', q_m) - u_m^1(q_f, q_m) \quad \text{for } q_f < q_f'.$$

This diminishes the additional transfers that the man is willing to pay to secure a match with a higher-type woman. At the same time, higher-type women experience a larger utility gap between matching with high-type and low-type men (see equation (7) for $g = f$), which raises the transfer needed to make a match with a low-type man acceptable to a high type-woman. Taken together, these forces weaken the incentives for upward rematching after job loss, leading to a shift toward downward rematching.

Conversely, if the cross-partial derivatives are negative, job loss increases a man's utility gain from matching with a higher-type woman, strengthening his willingness to pay a higher transfer to secure such a match. At the same time, higher-type women face a smaller utility gap between matching with high-type and low-type men, lowering the transfer they require to accept a low-type partner. These effects lead to upward rematching: displaced men tend to match with higher-type women and are willing to pay higher transfers to do so. In turn, due to these high transfers, high-type women are willing to accept their offers. This illustrates the intuition for parts *3.-a* and *3.-b* of Proposition 1.

Finally, it is important to note that even when displaced men re-match with higher-type women (i.e., under NAM), they do not experience welfare gains relative to non-displace men. This is because securing such a match requires paying a high transfer. As a result, a large share of the marital surplus goes to their new partner, and on average, they are left with lower welfare than in their previous match, which was formed before job loss.[27] Taken together, re-matching with a higher-earning woman mitigates, but does not eliminate or reverse the welfare loss from displacement for men. By contrast, women who separate following their partner's job loss, on average, do not experience a change in welfare: because their own type remains unchanged, their expected value of marriage after re-matching is equal to that in their previous match.

3 Empirical Strategy

This section describes the research design we use to estimate the treatment and selection effects introduced in Section 2.5. We use these empirical estimates to test the predictions of our conceptual framework and assess which modeling assumptions are consistent with the estimated combination of treatment and selection effects. Our research design compares 72,667 male workers who lose their jobs due to establishment closures with a control group of workers similar in observable characteristics but not affected

[27] To see this, note that the expected marital surplus for men of type q_m, averaged over the types of partners they match with, $\int_{\mathcal{M}(q_m)} S(q_f, q_m) dG_f(q_f)$, by Lemma 1 in Shimer and Smith (2000), is weakly increasing in q_m. This implies that the expected marital surplus is lower for men of type $q_m - d$ than for men of type q_m. This result holds even under NAM, where lower-type men (re)match with higher-type women.

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 used to construct the control group, and the main empirical specifications we estimate.

3.1 Data

Our empirical analysis draws on Danish register data covering the entire population living in Denmark between 1980 and 2007.[28] The data are drawn from tax and social security records and include individual-level information on a wide range of demographic characteristics, employment status, labor income, occupation, work hours, the firm and establishment in which the individual is employed, marital histories, and children. In particular, the data record whether an individual is married or in a cohabiting relationship and provide an identifier for the individual's spouse or cohabiting partner. Cohabiting couples are defined as two opposite-sex individuals who share the same address, are less than 15 years apart in age, have no family relationship, and do not share housing with other adults apart from their partner.[29]

3.2 Establishment Closures

We define a closing establishment as one that stops operating, i.e., sheds its entire workforce within three years.[30] The treatment year is defined as the first year in which a closing establishment sheds at least 10% of its workforce. The rationale for this definition is that layoffs occurring after this point are likely anticipated by the remaining workers. We exclude establishments with fewer than five employees in the treatment year. Our criteria yield 23,913 closing establishments. The average closing establishment employs 55 workers in the treatment year.

3.3 Treatment and Control Group

Treatment group We select the treatment group from men who are employed at a closing establishment in the treatment year and have at least three years of tenure. 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 (i.e. in $t = -3$).[31] 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 men who meet these criteria.[32]

[28]Our sample ends in 2007 due to a change in the definition of family types in the Danish registers.

[29]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 same-sex couples, so we do not include same-sex couples in our analysis.

[30]By focusing on establishment closures, we minimize endogeneity concerns that arise when layoffs selectively target workers based on performance or ability (see, e.g., Eliason and Storrie 2006).

[31]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.

[32]We repeat our empirical analysis for displaced women. The results are qualitatively identical to those for men but the estimates are less precise and, in some cases, statistically insignificant (see Section 4.6). Importantly, the point estimates for displaced women are fully consistent with our model and the conclusions we draw based on it.

Coarsened exact matching to select control group To construct a control group, we draw from men who, during the sample period, were never employed at an establishment within three years of its closure. We impose the same restrictions as for the treatment group on age, tenure, and relationship status, and also exclude men who work at the same establishment as their partner.

From this pool, we select one control individual for each treated individual using a coarsened exact matching (CEM) algorithm (Iacus, King, and Porro, 2012, 2019). The algorithm selects a control individual who, in the treatment year, provides an exact match on a set of observed characteristics. To make exact matching feasible, continuous variables are coarsened into discrete bins, and each treated individual is matched with a control whose characteristics fall into the same bin across all observables.[33]

Our CEM algorithm matches on marital status (single, cohabiting, married, divorced), age, children (binary indicator), calendar year, occupation (6 categories), industry (9 groups), establishment size quintiles, and tenure quintiles. Matching is performed three years prior to establishment closure for all variables, except establishment size, which is matched five years prior to closure.[34] Our empirical analysis is based on a combined sample of 72,667 displaced men in the treatment group and an equal number of men in the control group. For men in the control group, we refer to the year in which their 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 and has 12.6 years of education, roughly corresponding to a high school or vocational degree. In the year before displacement, workers in the treatment group and the control group earn annual salaries of 326,247 DKK and 324,898 DKK, respectively.[35] The female partners of men in the treatment and control groups are, on average, 36 years old, have 12.2 and 12.3 years of education, and earn annual salaries of 177,682 DKK and 178,891 DKK, respectively. In sum, Table B.1 confirms that the treatment and control groups are well balanced on observables, including those that our CEM algorithm does not match on, such as own labor income and the partner's labor income, age, and education.

3.4 Estimating Equations

We now introduce the empirical specifications used to estimate the treatment and selection effects described in Section 2.5. We begin with a standard difference-in-differences specification to estimate the impact of job displacement on labor market outcomes and relationship status. To study how job displacement affects rematching patterns, we use a second specification that compares the partners men match with

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

[34]We match on establishment size five years before closure because differences between the treatment and control groups begin to emerge in this variable three years prior to closure.

[35]Throughout, all monetary values are CPI-adjusted to 2004 DKK.

before and after displacement. Since this comparison is only meaningful for men who change partners, we estimate this specification on the sample of men who re-partner within the considered event-time window.[36]

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:

$$Y_{it} = \alpha + \sum_{\tau=-5}^{10} \psi_\tau \mathbb{1}\{t = \tau\} + \sum_{\tau=-5}^{10} \phi_\tau D_i \mathbb{1}\{t = \tau\} + \phi_D D_i + e_{it}, \tag{8}$$

where Y_{it} denotes the outcome for individual i in year t, measured relative to the year of actual or placebo displacement. D_i is an indicator for 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, ϕ_τ, capture differential changes in outcomes over event-time in the treatment group relative to the control group. The key identifying assumption is that absent job displacement, outcomes in the treatment and control group would have followed parallel trends.

Difference-in-differences specification conditional on rematching To estimate how job displacement affects rematching patterns, we use the following difference-in-differences specification, conditional on rematching. We consider the sample of all partners who are matched with a treatment or control individual between $t = -5$ and $t = 10$. Let j denote the partner for whom we observe the outcome Y_{jt}, and let i denote the corresponding treatment or control group individual matched with j in period t.[37] We define an indicator variable $D_{i(j)}$, which equals 1 if the individual i matched with j belongs to the treatment group. We also define an indicator variable $Post_{ij}$, which equals 1 if the match between i and j was formed after i's (actual or placebo) displacement.

We then estimate the following regression:

$$Y_{jt} = \alpha + \psi Post_{ij} + \gamma D_{i(j)} Post_{ij} + \phi_D D_{i(j)} + e_{jt}. \tag{9}$$

The coefficient ϕ_D captures differences between partners of treatment and control group individuals in matches formed prior to (actual or placebo) displacement. The coefficient ψ captures general differences between partners matched before and after displacement. The key coefficient of interest, γ, captures whether the difference in partner characteristics between the treatment and the control group changes as

[36] Conditioning on re-partnering aligns our empirical estimates with the model analog to which we compare them,

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

which also conditions on separation ($D_B = 1$) and rematching ($D_R = 1$) following displacement (see Section 2.5). Both the empirical estimate and the model analog capture the selection effect, whereby job displacement changes the composition of singles who rematch, as well as the treatment effect on the type of partner a given man matches with.

[37] We exclude partners who are matched with one treatment or control group individual at one point in time and with a different treatment or control group individual at another point in time (0.05% of our sample) because in that case the function $i(j)$ is not well defined.

we move from pre- to post-displacement matches. This specification identifies γ under the assumption that, absent job displacement, matching patterns would have evolved similarly across the two groups.

4 Empirical Results

This section presents our empirical results. We document four main findings: (i) job displacement increases the risk of relationship dissolution; (ii) job displacement induces relationship dissolution particularly among men matched with low-earning women; (iii) displaced men are more likely to remain single after a breakup than non-displaced men; (iv) displaced men are more likely to transition to higher-earning partners following a breakup, relative to non-displaced men. Section 4.1 documents the long-run effect of job displacement on employment and earnings. Sections 4.2–4.4 present the main empirical findings. Section 4.5 confronts theory and evidence. Section 4.6 provides several robustness checks: we rule out that our findings are driven by endogenous labor supply responses, replicate the analysis for displaced women, and show that the relocation of men to more favorable marriage markets does not explain our results. Finally, we provide back-of-the-envelope calculations suggesting that establishment closures are unlikely to induce substantial equilibrium effects in marriage or labor markets.

4.1 Labor Market Outcomes

We begin by documenting the effects of job displacement on employment and earnings. Following displacement, men's labor incomes drop sharply and remain persistently low. Figure 1A presents estimates of ϕ_τ from equation (8), which capture the differential evolution of labor income in treatment and control group after actual or placebo displacement. The trend in labor income prior to displacement is flat, followed by a pronounced drop post-displacement, reaching $-17,354$ DKK in $t = 3$, a 5% decline relative to men's average earnings in $t = -3$. Labor income remains depressed for at least ten years thereafter. The average effect over the post-displacement event-time window is $-13,332$ DKK, a -4% decline relative to men's average earnings in $t = -3$.[38] The long-run effect, measured in $t = 10$, is $-9,925$ DKK, or -3% of men's average earnings in $t = -3$. Figures 1B and B.1A and B show that the long-run decline in labor income is primarily driven by men transitioning to jobs with lower hourly wages, and to a lesser extent by reductions in work hours and employment.

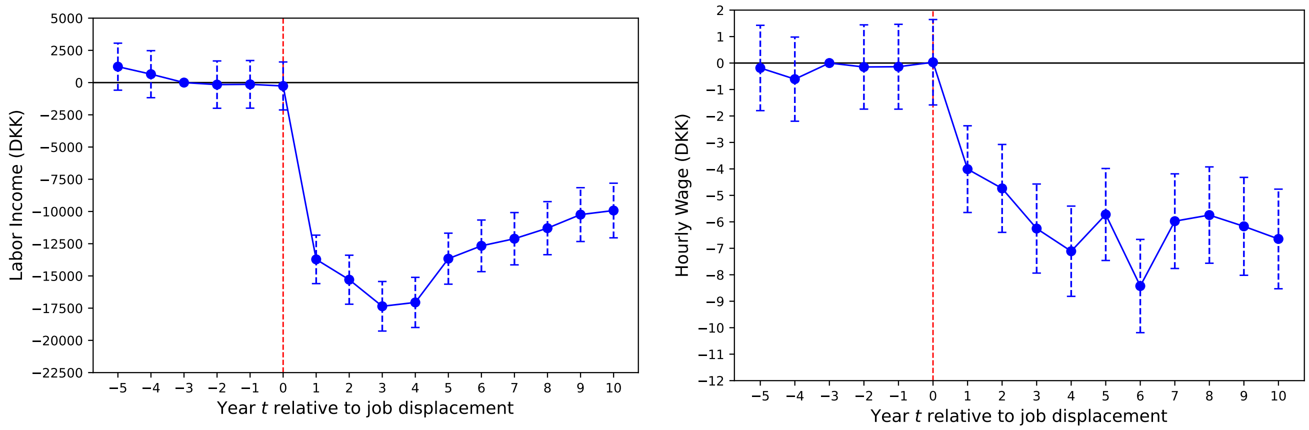
4.2 Relationship Status

Next, we examine how job displacement affects relationship status. Displacement increases the risk of relationship dissolution, and displaced men are more likely to remain single after a breakup than non-displaced men. 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).

[38]The average effect over the post-displacement event-time window is computed as $\frac{1}{10}\sum_{\tau=1}^{10}\phi_\tau$.

Figure 1: Labor Market Outcomes of Displaced Men:
Labor Income and Hourly Wages

(A) Labor Income (in DKK) (B) Hourly Wage (in DKK)



Notes: The figure shows the impact of job displacement on annual labor income (Panel A) and hourly wages (Panel B). Labor income includes zeros for nonemployed individuals, while hourly wages are conditional on employment. Both outcomes are measured in DKK (CPI 2004). Dashed vertical lines around each point estimate represent 95% confidence intervals. The estimates correspond to ϕ_τ from Equation (8). All results are based on a sample of men displaced due to establishment closures between 1980 and 2007, and a matched control group selected via coarsened exact matching. Sample selection criteria and the matching algorithm are described in Subsection 3.3.

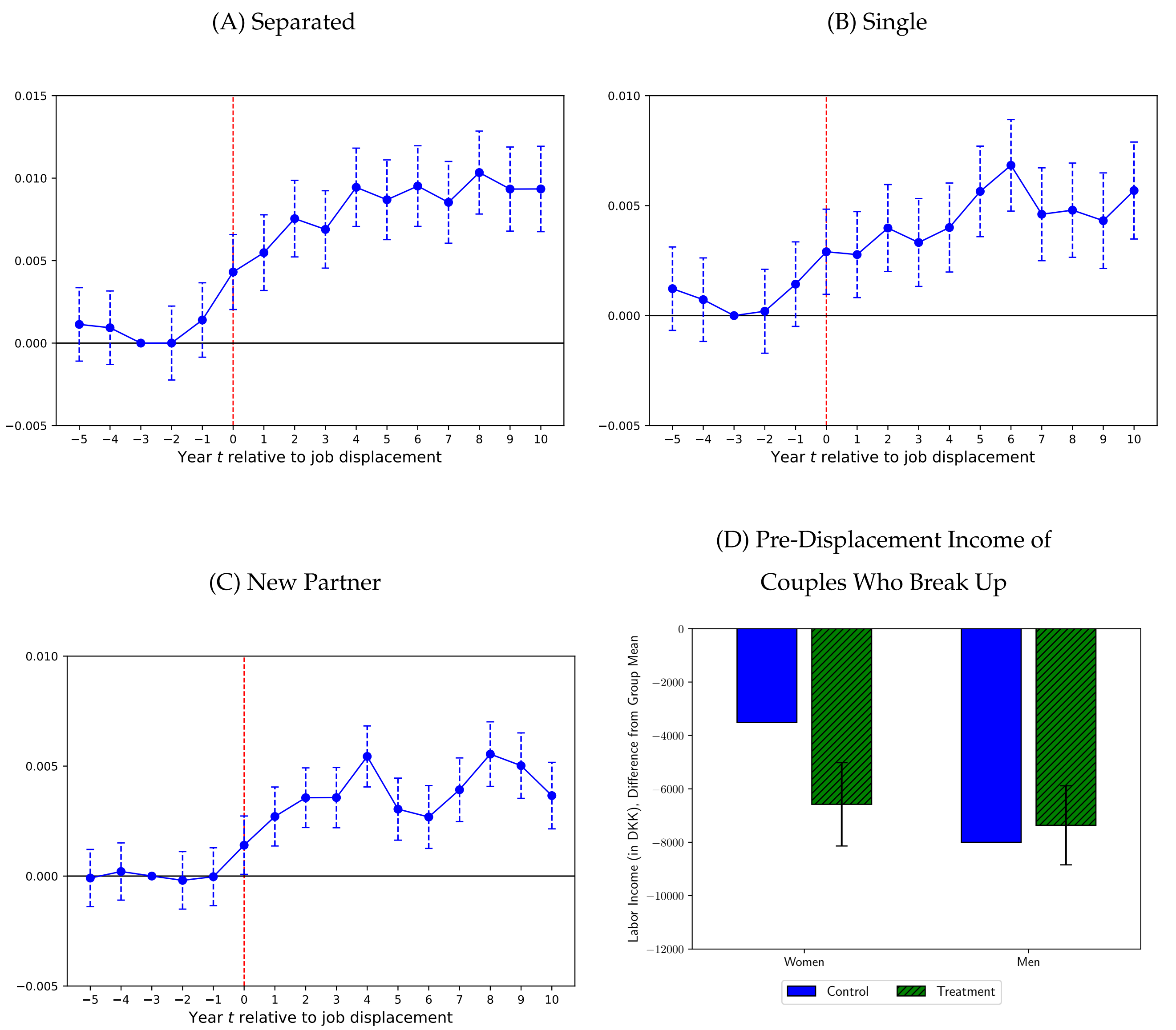
Figure 2A reports the effect on separations, using an indicator for not living with the same partner as in $t = -3$ as the outcome variable.[39] We find a statistically significant increase in separations following job displacement, reaching 0.01 by $t = 10$, a 6% increase relative to the control group's separation rate of 0.18 over the same time period.[40] This empirical result is consistent with the predictions of our conceptual framework under both PAM and NAM, which state that job displacement increases the risk of relationship dissolution (see prediction *1.* in Proposition 1).

Figure 2B and C decompose the effect of job displacement on separation into being single and living with a new partner. We use indicators for not living with a partner (Panel B) and for living with a partner different from the one in $t = -3$ (Panel C) as outcome variables. Both effects are statistically significant. By construction, the estimates sum to the overall effect on separations, with approximately two-thirds of the increase driven by men who are single post-breakup, and one-third by men living with new partners. We also compare the likelihood of remaining single post-breakup between actually and placebo-displaced men. Table B.2 reports differences between the two groups 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 finding a partner at any point during $t = 1, ..., 10$ after having been single for at least one period. Displaced men are statistically significantly less likely to transition out of being single by either measure. These estimates reflect both selection and treatment, i.e., both changes in the composition of singles and in a given man's likelihood of rematching, in response to job displacement.

[39] This includes both not cohabiting with any partner and living with a new partner different from the $t = -3$ partner.

[40] Huttunen and Kellokumpu (2016) and Eliason (2012) report comparable findings for Finland and Sweden, respectively.

Figure 2: Relationship Status of Displaced Men and
Pre-Displacement Income of Couples Who Break Up



<u>Notes:</u> Panels A–C show the effects of men's job displacement on different measures of relationship status. Panel A displays the effect on the probability of being separated from the pre-displacement partner, defined as the partner at $t = -3$. Panel B shows the effect on the probability of being single (i.e., unmarried and not cohabiting), and Panel C shows the effect on the probability of being matched (married or cohabiting) with a new partner who is distinct from the pre-displacement partner. Dashed vertical lines around point estimates indicate 95% confidence intervals. The values in Panels A–C correspond to coefficient estimates of ϕ_τ from Equation (8). Panel D displays the pre-displacement labor income of women and men who experience a breakup. Each bar represents average labor income in $t \in \{-5, \ldots, -3\}$ (before the male partner's actual or placebo displacement) for individuals who separate between $t = 0$ and $t = 10$ (after the male partner's actual or placebo displacement). All values in Panel D are differences from the respective (treatment or control) group mean. 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.

While our conceptual framework does not yield a sharp prediction about the effect of job displacement on the probability of remaining single (see prediction *2.* in Proposition 1), it is worth noting that our empirical estimates are not at odds with the model. Importantly, both the empirical estimates and the model capture treatment and selection effects, allowing for a meaningful comparison.

4.3 Post-Displacement Separation Patterns

Next, we examine how job displacement affects selection into relationship dissolution. To circumvent the direct effect of displacement on men's earnings, we measure couples' pre-displacement earnings in $t \in \{-5, .., -3\}$. We then compare couples in the treatment and control groups who separate within ten years following actual or placebo displacement. Figure 2D plots the average labor income of women and men who experience a breakup, separately for the treatment and control group, relative to the respective group means.[41] First, the figure shows that individuals who separate tend to have below-average earnings, regardless of gender or treatment status. Importantly, among couples who separate, women matched with displaced men have significantly lower earnings than those matched with control group men. The difference is statistically significant at -3063 DKK, 23% of the average income loss of a displaced man. This finding indicates that job displacement induces separations particularly among men matched with low-earning women, which aligns with the predictions of our conceptual framework under NAM but is inconsistent with those under PAM (see predictions *5.-a* and *5.-b* in Proposition 1).[42] By contrast, the difference in men's earnings between dissolving couples in the treatment and control group is modestly positive but statistically insignificant.

We repeat the analysis for outcomes other than labor income. Figure B.2 shows no statistically significant differences in age or number of children. Both women and men in dissolving couples in the treatment group have statistically significantly fewer years of schooling than those in the control group, but the differences are small (less than 0.05 years).

4.4 Rematching Patterns of Displaced Men

We now examine how job displacement affects the types of partners men rematch with after a breakup. Our findings show that displaced men are more likely than their control group counterparts to transition from low-earning to higher-earning partners. By contrast, we find no substantial differences in rematching patterns with respect to other partner characteristics, such as age or education. We begin by comparing the propensity to transition to a higher-, similarly-, or lower-earning new partner relative to the pre-displacement partner in the treatment and the control group. To this end, we estimate Equation (8) using three indicator variables as outcomes:

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

[41] Women are assigned to the treatment or control group according to their male partner's treatment status.

[42] To assess whether the conditions of prediction *5.-a* and *5.-b* are satisfied we additionally test whether $F(q_m|D_B = 1, D = 1)$ first order stochastically dominates $F(q_m|D_B = 1, D = 1)$ or vice versa. Figure B.3 plots the empirical CDF of labor income in $t \in \{-5, .., -3\}$ 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).

where Y_{it} denotes the earnings of the partner with whom individual i is matched in period t. Y_{it}^{pre} denotes the earnings of the partner with whom individual i was matched prior to displacement, in period $t = -3$. Importantly, we compare the earnings of pre- and post-displacement partners in the same time period t, so our estimates are not affected by time trends that affect both partners. Here, ρ denotes a threshold parameter, and $D_{R,it}$ indicates whether individual i is living with a partner different from the one in $t = -3$. According to this definition, Y_{it}^{+} indicates that individual i transitioned to a new partner who outearns his pre-displacement partner by at least $\rho \cdot 100\%$; Y_{it}^{0} indicates that the new partner's earnings fall within a $\pm\rho \cdot 100\%$ range of the pre-displacement partner's earnings; and Y_{it}^{-} indicates that the new partner earns at most $(1-\rho) \cdot 100\%$ of what the pre-displacement partner earned. For our main analysis, we set $\rho = 0.05$, and use annual labor income as the measure of earnings.[43]

Figures 3A–C present estimates of ϕ_τ from Equation (8), using Y_{it}^{+}, Y_{it}^{0}, and Y_{it}^{-} as outcome variables. The results show statistically significant increases in the likelihood of transitioning to higher- and similarly earning partners following job displacement, but no effect on transitions to lower-earning partners. By $t = 10$, the effects on transitions to higher- and similarly earning partners are 0.003 and 0.002, respectively, corresponding to increases of 8.5% and 5.3% relative to the control group. These results suggest that job displacement shifts rematching patterns toward higher-earning partners.

To provide a continuous measure of the change in rematching patterns following job displacement, we estimate specification (9). Table 1 reports estimates of γ, using annual labor income, hourly wages, and work hours as outcome variables.[44] The estimate in Column (1) shows that displaced men who transition to a new partner experience a statistically significant increase in partner earnings of 3,269 DKK relative to men in the control group. Scaling this estimate by the average income loss from job displacement $-13,332$ DKK (see Section 4.1), yields a ratio of -0.25. This implies that among men who experience a breakup and rematch with a new partner, a one-unit loss in their own income is associated with matching with a 0.25 unit higher earning partner.[45] Columns (2) and (3) of Table 1 present estimates using hourly wages and work hours as outcome variables, indicating that the estimated increase in partner income is driven by differences in partners' hourly wages rather than their labor supply. Taken together, our findings suggest that job displacement increases the likelihood that men transition from low-earning to higher-earning partners following a breakup. This pattern is consistent with the predictions of our conceptual framework under NAM but is at odds with those under PAM (see predictions *3.-a* and *3.-b* in Proposition 1). Note that both the empirical estimates and the model capture treatment and selection effects, allowing for a meaningful comparison.

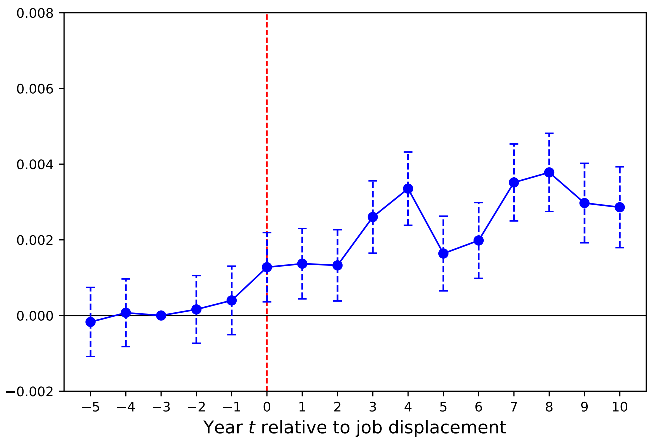
[43] Varying the value of ρ or using hourly wages instead of annual labor income yields qualitatively similar results. Figures B.4 and B.5 report results for $\rho = 0.1$ and for using hourly wages.

[44] While labor income is observed for our full sample, wages and work hours are only recorded for subsamples of the population. In particular, we observe hourly wages for jobs in the public sector and in private firms with at least 10 employees, whereas work hours are available only for the individual's main job in November (defined as the job with the highest income or hours that month), provided that the job was subject to pension contributions (ATP) (see Lund and Vejlin, 2016, for details).

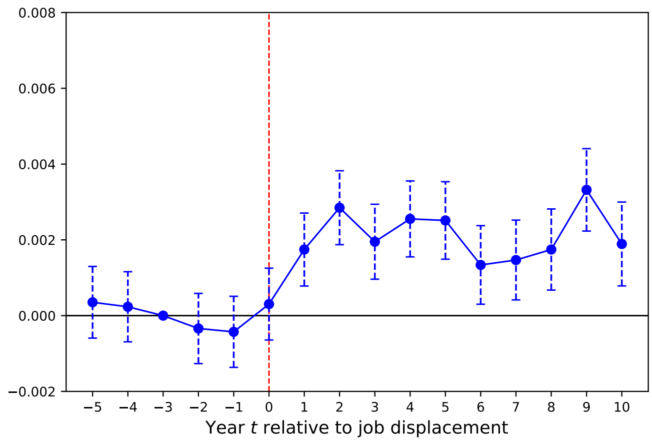
[45] If we instead scale the estimate by the long-run income loss from job displacement, $-9,925$ DKK, this yields a ratio of -0.33.

Figure 3: Rematching Patterns of Displaced Men:
New Partners' vs. Old Partners' Income

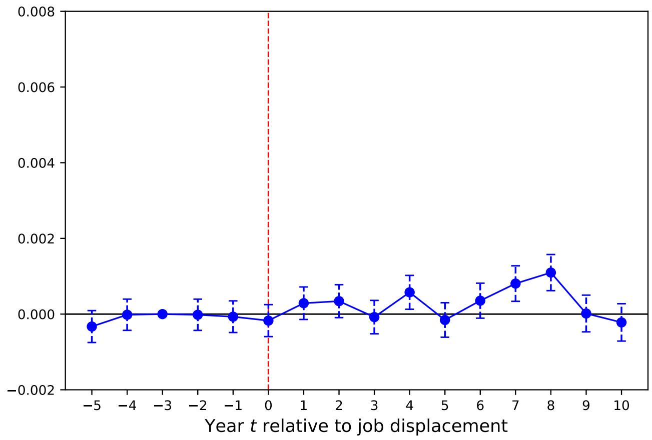
(A) New Partner's Income $\geq 5\%$ Higher than $t = -3$ Partner's Income



(B) New Partner's Income in $\pm 5\%$ Range of $t = -3$ Partner's Income



(C) New Partner's Income at least 5% Lower than $t = -3$ Partner's Income



Notes: The figure shows the effect of job displacement on the rematching patterns of men after a breakup. Panel A displays the effect on the probability of matching with a new partner with at least 5% higher labor income than that of the pre-displacement partner (defined as the partner at $t = -3$). Panel B shows the effect on the probability of matching with a new partner with labor income between –5% and +5% of the pre-displacement partner's labor income. Panel C shows the effect on the probability of matching with a new partner with at least 5% lower labor income than that of the pre-displacement partner. The estimates correspond to ϕ_τ from Equation (8). Dashed vertical lines around point estimates indicate 95% confidence intervals. All estimates are based on a sample of men displaced due to establishment closures between 1980 and 2007 and a control group selected by coarsened exact matching. Sample selection and matching procedures are detailed in Subsection 3.3.

To assess whether job displacement affects rematching patterns along other dimensions, we repeat the analysis using partner age, education (years of schooling), and the number of children from previous relationships as outcome variables. Table 2 shows that displaced men tend to rematch with younger partners who have more children. The estimated effects are statistically significant but modest in size: -0.27 years for age and 0.04 for number of children. The effect on partner education is small and statistically insignificant at -0.04 years.

Table 1: Rematching Patterns of Displaced Men:
New Partners' Income, Wage, and Work Hours

Partners' Outcomes	Labor Income	Wage	Work Hours
Treated $\times$ Post-Displacement, γ	3269.01**	4.03***	-0.12
	(1614.72)	(1.38)	(0.13)
No. of observations	108,982	60,362	53,702

Notes: The table shows the effect of men's job displacement on the types of partners they transition to, measured by partners' labor income, hourly wage (conditional on employment), and weekly work hours (including zeros for non-employed individuals). The table reports coefficient estimates of γ from Equation (9). Standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Rematching Patterns of Displaced Men:
New Partners' Age, Education, and No. of Children

Partners' Outcomes	Age	Education	No. of children
Treated $\times$ Post-Displacement, γ	-0.27***	-0.04	0.04***
	(0.09)	(0.03)	(0.01)
No. of observations	108,982	108,982	108,982

Notes: The table shows the effect of men's job displacement on the types of partners they transition to, measured by partners' age, education (years of schooling), and number of children. The table reports coefficient estimates of γ from Equation (9). Standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5 Contrasting Theory and Evidence

Having presented both the model predictions and the empirical evidence, we now discuss how they align. Table 3 provides a side-by-side comparison of the empirical findings from Sections 4.2–4.4 with the theoretical predictions derived in Proposition 1. The comparison shows that the empirical evidence from job displacement is consistent with our conceptual framework under NAM. Under PAM, by contrast, the framework predicts that men transition away from high-earning toward lower-earning women ($\gamma_{q_f|B} \geq 0$ and $\gamma_{\Delta q_f|R} \leq 0$), a pattern rejected by the data. At the same time, the cross-sectional correlation between matched partners' incomes in the data is positive (0.15), which is consistent with PAM but inconsistent with NAM (see Equations (5) and (6)).

Recall that, as an additional testable implication, our conceptual framework predicts that under PAM, $\gamma_{\Delta q_f|R}$ is not only weakly negative, but also bounded away from zero. To provide a simple empirical check of this implication, we approximate $\frac{\partial \mathbb{E}[q_f|q_m]}{\partial q_m}$ by the slope coefficient β, which we obtain from a regression of wives' income on husbands' income and a constant.[46] Under this approximation, prediction *4.-a* in

[46]As is well known, $\beta = \frac{Cov(q_f, q_m)}{Var(q_m)}$ provides the best linear predictor of $\frac{\partial \mathbb{E}[q_f|q_m]}{\partial q_m}$, i.e., it minimizes the mean squared prediction error between $\mathbb{E}[q_f|q_m]$ and its linear approximation $\alpha + \beta q_m$ (see, e.g., Goldberger 1991).

Proposition 1 simplifies to $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m} \geq \beta$, where the left-hand side captures the impact of job displacement on the rematching patterns of displaced men, scaled by the income loss from job displacement.[47] We estimated this ratio at -0.25 (see Section 4.4), whereas our estimate of β in the estimation sample is 0.17. These estimates are far from satisfying the quantitative restriction, $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m} - \beta \geq 0$, which is implied by our conceptual framework under PAM.

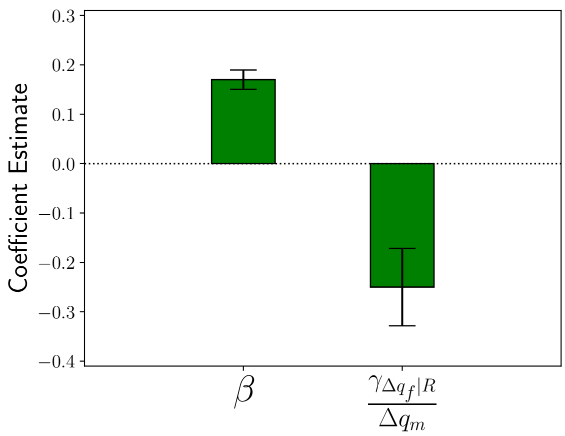
In summary, our empirical evidence from job displacements is consistent with our conceptual framework under NAM but not under PAM. By contrast, the positive cross-sectional correlation between matched partners' incomes is consistent with PAM, but not with NAM. Taken together, these findings imply that under one-dimensional matching with PAM or NAM, it is challenging to reconcile the evidence from job displacements with the positive correlation between matched partners' incomes.

Table 3: Contrasting Theory and Evidence

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

Notes: The table summarizes the predictions implied by our conceptual framework under NAM and PAM from Proposition 1 (in Section 2) and contrasts them with our empirical findings reported in Sections 4.2–4.4.

Figure 4: Correlational Evidence vs. Evidence from Establishment Closures



Notes: The figure displays the regression coefficient of regressing wife's on husband's income, β, alongside the effect of job displacement on the types of partners men transition to, measured by partners' labor income, $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m}$. Error bars indicate 95% confidence intervals.

[47]To see this, note that using $\frac{\partial \mathbb{E}[q_f|q_m]}{\partial q_m} \approx \beta$, we have $\overline{\gamma}_{\Delta q_f|R} \approx -d\beta = \Delta q_m \beta$. Dividing $\gamma_{\Delta q_f|R} \leq \Delta q_m \beta$ by $\Delta q_m \leq 0$ yields $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m} \geq \beta$.

4.6 Robustness and Additional Results

This subsection presents robustness checks and additional results that support our main findings. First, we show that the results are not driven by endogenous adjustments in partners' labor supply. Second, we provide analogous results for women who experience job displacement. These results are qualitatively similar to the findings for men but estimated with less precision. Third, we rule out that our findings are explained by men relocating to municipalities with a high concentration of high-earning single women or where single men are scarce relative to single women. Finally, back-of-the-envelope calculations suggest that establishment closures are unlikely to generate substantial equilibrium effects in either the marriage market or the labor market.

Endogenous Labor Supply A potential concern is that labor income is not an exogenous trait, as it is directly influenced by endogenous labor supply decisions. This raises the question to what extent our empirical findings are driven by partners who endogenously adjust their work hours. However, our empirical results for labor income, work hours, and hourly wages show that endogenous labor supply adjustments do not appear to be the primary driver of our findings. In particular, Figure B.5 shows that the main patterns hold when we consider hourly wages as the outcome, for which this concern is less relevant. Moreover, Table 1 shows that our empirical finding (iv) is driven by men partnering with women who have higher hourly wages (significant coefficient for hourly wages), not by differences in work hours choices (negative and statistically insignificant coefficient for work hours).

Results for Displaced Women It is interesting to ask whether the patterns we document for displaced men also hold for women. To explore this, we repeat our main empirical analyses for female workers who experience job displacement. Figures B.7, B.8 and Table B.3 report the results. The findings are qualitatively the same as for men: displaced women are more likely to experience a break up and to transition from a low-earning to a higher-earning male partner, relative to the matched control group of non-displaced women (see Figure B.8 and Table B.3). However, the estimates are less precise than those for men, and in some cases not statistically significant. It is also worth noting that the impact of job displacement on women's labor income and hourly wages is smaller in magnitude and less persistent than the corresponding effects for men (see Figure B.7).

Moves Across Municipalities and Local Marriage Market Conditions We examine whether job displacement affects residential mobility and, if so, whether such moves are directed toward municipalities with more favorable marriage market conditions for men. Figure B.6A presents estimates of Equation (8), using as the outcome an indicator for whether the individual resides in a different municipality than in $t = -3$ (i.e., before the actual or placebo displacement). Displacement leads to a statistically significant increase in the likelihood of having moved by 1.16 percentage points after 10 years. To assess whether these are moves to municipalities with favorable marriage market conditions, we consider two additional outcomes:

the average earnings of single women in the municipality, and the local sex ratio, defined as the number of single women divided by the number of single men. Figures B.6B and C show no statistically significant effect of displacement on either variable, suggesting that men do not systematically relocate to areas with more favorable marriage market conditions.

Labor Market and Marriage Market Equilibrium Effects of Establishment Closures We assess the likelihood that establishment closures exert notable labor-market or marriage-market equilibrium effects by using a back-of-the-envelope calculation. The average closing establishment in our sample employs 55 workers, 0.6% of the average local labor force in municipalities with an establishment closure. 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 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. We conclude that the inflows of displaced workers into the labor market and of newly single individuals into the marriage market are relatively small and, therefore, unlikely to generate general equilibrium effects.

5 Reconciling Theory and Evidence: Multidimensional Matching

This section shows that multidimensional matching provides a potential explanation for our empirical findings. Our one-dimensional conceptual framework under PAM or NAM cannot simultaneously account for two key empirical patterns: (i) our finding that men transition from low-earning to higher-earning partners following job displacement, and (ii) the positive cross-sectional correlation between matched partners' incomes. While NAM implies the first pattern, it contradicts the second. The opposite holds under PAM (see Section 4.5). We now show that extending the framework to multidimensional matching can resolve this tension. Intuitively, if job displacement affects only certain dimensions of an agent's type (such as earnings potential or health), then sorting along those dimensions will shape rematching patterns following displacement. By contrast, the cross-sectional correlation between partners' types may be governed by sorting on other dimensions that are unaffected by displacement (such as age or height). In the following subsections, we define notions of multidimensional sorting, and show formally that multidimensional matching can simultaneously explain both empirical patterns.

5.1 Multidimensional Sorting

We consider the framework described in Section 2.1 for the multidimensional case, $K > 1$. The 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.

We extend the definitions of one-dimensional sorting by Shimer and Smith (2000) (see Appendix A) to the multidimensional setting by defining PAM and NAM dimension by dimension (see Lindenlaub and Postel-Vinay, 2023). Let $\mathcal{M}(q_m) = \{q_f \in Q_f : S(q_f, q_m) \geq 0\}$ denote the multidimensional matching set for an agent of type q_m. At times, it will be useful to write $q_f = (q_{fi}, q_f^{-i})$, where q_{fi} is the i-th component of the vector q_f, and q_f^{-i} denotes the remaining components. We define positive and negative assortative mating in dimension i, denoted by PAM(i) and NAM(i), as follows:

Definition 1. *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 $(q'_{fi}, q_f^{-i}) \in \mathcal{M}(q''_{mi}, q_m^{-i})$.

We show that under either PAM(i) or NAM(i), there is a (weakly) monotonic relationship between the matching sets and the i-th component of an agent's type, extending the corresponding one-dimensional result by Shimer and Smith (2000) to the multidimensional setting. To establish this result, we impose the following additional assumption, which ensures 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, Assumption A-1 requires that for any man of type q_m and any woman with characteristics q_f^{-i}, there exists a value of q_{fi} sufficiently favorable that the two would agree to match upon meeting. Leveraging this assumption, 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 $\mathcal{M}(q_m)$ forms an interval with bounds that are weakly increasing in q_{mi} under PAM(i) and weakly decreasing under NAM(i).

5.2 Job Loss and Multidimensional Marriage Market Dynamics

We now link the multidimensional framework to our empirical setting by modeling job displacement as a permanent, unexpected reduction in the i-th dimension of a displaced agent's type. Formally, we assume that a man of type q_m who is displaced from his job experiences a permanent reduction in q_{mi} to $q_{mi} - d < q_{mi}$, while all other components of q_m remain unchanged. Similar to the one-dimensional case, we assume that q_{mi} maps into an agent's earnings potential.[48]

To derive predictions about 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 during the interval $[t_0, \tau]$). The definitions of the effects of job displacement on the separation risk and the probability of remaining single, γ_B and $\gamma_{R=0|B}$, carry over from Section 2.5. We further define:

$$\begin{aligned}
\gamma_{q_{mi}|B} &= \mathbb{E}\left[q_{mi}(t_0)|D_B = 1, D = 1\right] - \mathbb{E}\left[q_{mi}(t_0)|D_B = 1, D = 0\right], \\
\gamma_{q_{fi}|B} &= \mathbb{E}\left[q_{fi}(t_0)|D_B = 1, D = 1\right] - \mathbb{E}\left[q_{fi}(t_0)|D_B = 1, D = 0\right], \\
\gamma_{\Delta q_{fi}|R} &= \mathbb{E}\left[q_{fi}(\tau) - q_{fi}(t_0)|D_R = 1, D_B = 1, D = 1\right] - \mathbb{E}\left[q_{fi}(\tau) - q_{fi}(t_0)|D_R = 1, D_B = 1, D = 0\right]
\end{aligned}$$

in direct analogy to the corresponding objects defined in Section 2.5. We now derive predictions regarding these treatment and selection effects of job displacement, mirroring the one-dimensional case.

Proposition 2. *Consider the multidimensional case, $K > 1$, of the described search and matching environment in steady-state equilibrium, and suppose Assumption 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: $\gamma_{\Delta q_{fi}|R} \leq 0$.*

[48] Other attributes, in addition to labor income, may also be functions of q_{mi} and thus be affected by job displacement. The distinguishing feature of the multidimensional case is that there are additional dimensions $j \neq i$ of q_m that are not affected by job displacement. The idea is that while some 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), others, such as an agent's age or height, remain unchanged.

4.-a The association between job displacement and partner type is bounded above: $\gamma_{\Delta q_{fi}|R} \leq \overline{\gamma}_{\Delta q_{fi}|R}$.
The upper bound is given by

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

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 non-displaced men separate:* $\gamma_{q_{fi}|B} \geq 0$.

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

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

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 from Proposition 1 extend to the multidimensional case. In particular, it shows that NAM(i) implies that men transition from low-earning to higher-earning partners following job displacement, one of the two empirical patterns motivating our analysis.

5.3 How Multidimensional Sorting Shapes Cross-Sectional Correlations

We now analyze under which conditions the multidimensional framework generates a positive cross-sectional correlation between matched partners' incomes. We show that a positive correlation in dimension i can arise even under NAM(i) if indirect effects from sorting in other dimensions dominate. This result implies that multidimensional matching can reconcile the two empirical patterns: displaced men transition to higher-earning partners (as implied by NAM(i); see Proposition 2), and the correlation of matched partners' incomes is positive.

Formally, Proposition 3 establishes conditions under which the conditional expectation $\mathbb{E}[q_{fi}|q_{mi}]$ is weakly increasing (decreasing) in q_{mi}, implying a weakly positive (negative) correlation between q_{fi} and q_{mi}. To establish this result, we impose 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:*

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

Intuitively, A-2 is satisfied if there is a trade-off between q_{fi} and q_{fj}: for a man of type q_m, matches with women who have a high value in one dimension and a low value in the other are more likely than matches with women who have high values in both dimensions or low values in both dimensions.

For simplicity, we state Proposition 3 for the special case $K = 2$. The result for the general multidimensional case $K > 1$ requires additional notation and further assumptions on the joint distribution of q_m^{-i}, and is provided in Proposition 4 in Appendix A.[49]

Proposition 3. *Consider the bidimensional case, $K = 2$, of the described search and matching environment in steady-state equilibrium, and suppose Assumptions A-1 and A-2 hold.*

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

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

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

$$\begin{aligned} PAM(i) &\Rightarrow DE \geq 0, \\ NAM(i) &\Rightarrow DE \leq 0. \end{aligned}$$

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

$$\begin{aligned} PAM(j) \text{ and } G(q_{mj}|q_{mi}) \text{ is weakly decreasing in } q_{mi} &\Rightarrow IE \geq 0, \\ NAM(j) \text{ and } G(q_{mj}|q_{mi}) \text{ is weakly decreasing in } q_{mi} &\Rightarrow IE \leq 0, \\ PAM(j) \text{ and } G(q_{mj}|q_{mi}) \text{ is weakly increasing in } q_{mi} &\Rightarrow IE \leq 0, \\ NAM(j) \text{ and } G(q_{mj}|q_{mi}) \text{ is weakly increasing in } q_{mi} &\Rightarrow IE \geq 0. \end{aligned}$$

Proposition 3 decomposes the dependence of $\mathbb{E}[q_{fi}|q_{mi}]$ on q_{mi} into two components. The direct effect (DE) captures the impact of increasing q_{mi} while holding the man's other attributes, q_m^{-i}, fixed. The indirect effect (IE) captures the association between q_{fi} and q_{mi} that arises from sorting on the remaining attributes q_m^{-i}. The proposition provides sufficient conditions for the sign of each component, and thereby for whether $\mathbb{E}[q_{fi}|q_{mi}]$ is increasing or decreasing in q_{mi}, implying $Corr(q_{fi}, q_{mi}) \geq 0$ or $Corr(q_{fi}, q_{mi}) \leq 0$, respectively. Importantly, the result shows that a positive cross-sectional correlation between q_{fi} and q_{mi} is possible if the indirect effect is positive and dominates in magnitude.

[49] The condition that $G(q_{mj}|q_{mi})$ is weakly increasing in q_{mi} (sometimes referred to as *positive regression dependence*) implies a weakly positive correlation, $Corr(q_{mj}, q_{mi}) \geq 0$ (see, e.g., Lehmann 1966).

5.4 Summary

Propositions 2 and 3 show that multidimensional matching can simultaneously account for the two empirical patterns that motivate our analysis: men tend to transition from low-earning to higher-earning partners following job displacement, and partner incomes are positively correlated in the cross-section.

Proposition 2 formalizes that job loss leads to transitions away from low-earning and toward higher-earning partners under negative sorting on earnings potential (extending Proposition 1 to the multidimensional case). Proposition 3 shows that a positive cross-sectional correlation in partner incomes can nonetheless arise if indirect effects from sorting on other traits dominate. Taken together, these results illustrate how multidimensional matching can reconcile both empirical patterns. In contrast, the two patterns are mutually exclusive in one-dimensional models (see Proposition 1).

6 Implications

This section explores implications of our findings for understanding marriage market matching. In particular, we contrast the multidimensional matching framework, which aligns with our empirical results, with the standard one-dimensional model under PAM that is not supported by our evidence. In Section 6.1, we argue that our multidimensional framework helps reconcile the positive cross-sectional correlation in spouses' earnings with Becker's (1973) seminal theory of marriage markets, which predicts negative sorting on wages. Section 6.2 demonstrates that our findings imply an important role for sorting on unobserved characteristics. Section 6.3 illustrates the quantitative relevance of our findings by comparing counterfactual simulations in the one-dimensional model and a bidimensional specification of our framework.

6.1 Implications for Interpreting Empirical Matching Patterns

The positive cross-sectional correlation between partners' incomes is often interpreted as evidence of positive sorting on income. This interpretation contrasts with a prediction of Becker's seminal theory, which assumes that partners' incomes are substitutes and therefore predicts negative sorting on wages, as this maximizes the gains from specialization within the household (Becker, 1973, 1981).

Various arguments have been put forward to resolve the apparent discrepancy between the empirical positive correlation in spouses' wages and the theoretical prediction of negative sorting. Becker (1981) argues that missing wage data for non-working women may bias the observed correlation toward positive values. Lam (1988) shows that joint consumption of a market-purchased good that is public within the household can give rise to positive sorting (see also Low 2024). Recently, complementarities in spouses' housework hours (e.g., 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 used as mechanisms to generate earnings-based positive sorting.

Our findings offer an alternative perspective. In our multidimensional framework, sorting on income, conditional on other dimensions of agent type, is negative. This is consistent with the prediction of Becker's theory, in which partners' incomes are substitutes and couples match to maximize gains from specialization. At the same time, in our framework, a positive cross-sectional correlation in partners' income may arise through indirect effects of sorting on other characteristics, for example driven by education homophily (see, e.g., Chiappori et al. 2009, 2018) or homophily on other traits. Importantly, in the multidimensional framework, forces toward negative sorting on income and positive sorting on other characteristics do not counteract each other, but jointly shape matching patterns. As a result, unconditional correlations in matched partners' characteristics reflect sorting across all dimensions. In contrast, leveraging exogenous variation in one characteristic, while holding all others fixed, allows inference about sorting along that dimension.

6.2 The Role of Unobserved Characteristics in Shaping Observed Matching Patterns

We now decompose the empirical association between spouses' incomes into the shares driven by observed characteristics and a residual attributable to unobserved characteristics. Consider the regression

$$y_f = \beta_0 + \beta_1 y_m + \beta_2' X_m + \beta_3' X_f + \epsilon \tag{10}$$

where y_f and y_m denote the labor income of the female and male partner in a couple, and X_f, X_m are vectors of characteristics other than income. Interpreted through the lens of the multidimensional matching framework, our evidence from job displacements suggests that sorting on income, conditional on all other characteristics, is negative. The coefficient β_1 reflects this direct negative effect, but also captures the indirect effect arising from sorting on unobserved characteristics omitted from the regression. β_1 thus provides a lower bound on the contribution of this indirect effect to the empirical association between partners' incomes.[50]

In Table 4, we report estimates from regression (10), varying the set of variables included in X_m and X_f. The "raw" coefficient estimate of β_1 obtained by regressing the female partner's income on the male partner's income without controls is 0.16. Controlling for age fixed effects for both partners reduces the

[50]Formally, suppose the multidimensional agent types are $q_f = (y_f, X_f, U_f)$ for women and $q_m = (y_m, X_m, U_m)$ for men, where U_f, U_m are characteristics omitted from the regression. Regression (10) estimates the conditional mean $\mathbb{E}[y_f|y_m, X_m, X_f]$, whose slope can be decomposed into a direct and an indirect effect, analogous to Proposition 3:

$$\mathbb{E}[y_f|y_m'', X_m, X_f] \quad - \quad \mathbb{E}[y_f|y_m', X_m, X_f] = \text{DE} + \text{IE},$$

where

$$DE \quad = \quad \int \mathbb{E}[y_f|y_m'', X_m, U_m, X_f, U_f] - \mathbb{E}[y_f|y_m', X_m, U_m, X_f, U_f] dG(U_f, U_m|y_m'', X_m, X_f)$$

and

$$\begin{aligned} IE \quad = \quad & \int \mathbb{E}[y_f|y_m', X_m, U_m, X_f, U_f] dG(U_f, U_m|y_m'', X_m, X_f) \\ & - \int \mathbb{E}[y_f|y_m', X_m, U_m, X_f, U_f] dG(U_f, U_m|y_m', X_m, X_f). \end{aligned}$$

Given that sorting on income conditional on other characteristics is negative (i.e., under NAM(1)) it follows that DE ≤ 0 and therefore $\mathbb{E}[y_f|y_m'', X_m, X_f] - \mathbb{E}[y_f|y_m', X_m, X_f] \leq IE$, which implies in the limit that $\beta_1 \leq$ IE.

estimate by 0.019 (12%), while controlling for education fixed effects reduces it by 0.077 (48%). Including both sets of fixed effects reduces the estimate by 0.099 (56%) to 0.071. Given that β_1 is a lower bound on the indirect effect of sorting on unobserved characteristics, it follows that at least 44% $(= 0.07/0.16 \cdot 100\%)$ of the raw coefficient estimate reflects sorting on unobserved characteristics omitted from the regression (that is, characteristics other than income, age, and education).[51]

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

	(1)	(2)	(3)	(4)
Husband's labor income ($\hat{\beta}_1$)	0.160***	0.141***	0.083***	0.071***
	(0.000558)	(0.000523)	(0.000539)	(0.000571)
Covariates				
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	3,034,432	3,034,432	3,034,432	3,034,432

Notes: This table reports coefficient estimates of β_1 from equation (10) 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.3 Counterfactual Simulations: Marital Sorting and Income Inequality

This section explores the implications of our findings for how marital sorting shapes the relationship between individual- and household-level income inequality. We simulate a rise in individual-level income inequality in calibrated one-dimensional and bidimensional versions of our framework to illustrate how the dimensionality of marital sorting affects this relationship. The remainder of the section describes the model specifications, the calibration, and our simulation results.

Model Specification To calibrate our framework, we impose additional functional form and distributional assumptions, and extend the framework to include a match specific "love shock", z, which captures non-economic motives for marriage.[52] In the 1D specification, individuals match on incomes, q_f and q_m. In the 2D specification, they match on income, q_{f1} and q_{m1}, and on a residual characteristic, q_{f2} and q_{m2}, which captures all remaining traits, including unobserved characteristics. We denote the correlation

[51]This may include characteristics such as anthropometrics (Oreffice and Quintana-Domeque, 2010), personality traits (Dupuy and Galichon, 2014), tobacco use (Chiappori, Oreffice, and Quintana-Domeque, 2017a), or physical attractiveness (Fisman, Iyengar, Kamenica, and Simonson, 2006), which are unavailable in the Danish register data but have been found to matter for marriage market matching in other studies.

[52]The love shock is drawn from a $N(\mu_z, \sigma_z)$ distribution upon meeting a potential partner, is equal for both partners, and remains unchanged for the duration of a match. It allows the model to generate empirically plausible matching patterns. Without it, income would fully determine matching in the 1D model. See Jacquemet and Robin (2013), Goussé et al. (2017), and Borovicková and Shimer (2024).

between income and the residual characteristic by ρ. We specify the flow utilities of married and single individuals as follows:

$$\text{1D model:} \quad \begin{aligned} \text{Couples:} \;\; u_g^1(q_f, q_m) &= \kappa_1 \tfrac{(q_f+q_m)^{1-\eta}}{1-\eta} - \kappa_2 (q_f - q_m)^2 + z \\ \text{Singles:} \;\; u_g^0(q_g) &= \kappa_1 \tfrac{q_g^{1-\eta}}{1-\eta}, \quad g \in \{f, m\} \end{aligned} \tag{11}$$

$$\text{2D model:} \quad \begin{aligned} \text{Couples:} \;\; u_g^1(q_f, q_m) &= \omega_1 \tfrac{(q_{f1}+q_{m1})^{1-\eta}}{1-\eta} - \omega_2 (q_{f2} - q_{m2})^2 + z \\ \text{Singles:} \;\; u_g^0(q_g) &= \omega_1 \tfrac{q_{g1}^{1-\eta}}{1-\eta} \quad g \in \{f, m\}, \end{aligned} \tag{12}$$

In both models, the first term in $u_g^1(q_f, q_m)$ induces negative sorting when $\eta > 0$.[53] Intuitively, the marginal utility of partner income declines with own income, which generates incentives that support NAM. The second term in $u_g^1(q_f, q_m)$ captures homophily by penalizing unequal matches, thereby creating incentives for positive sorting.[54] The relative magnitudes of κ_2 and κ_1 in the 1D model, and of ω_2 and ω_1 in the 2D model, determine which of these incentives dominates. The key distinction between the model versions is that the homophily term penalizes income differences in the 1D model, but differences in residual characteristics in the 2D model. This creates incentives for positive sorting on income in the 1D model, and on residual traits in the 2D model. Finally, the flow utility of singles only depends on own income in both models. Further details about the model specification (including type spaces, matching technology, household bargaining, equilibrium characterization, and numerical solution procedure) are provided in Appendix C.

Calibration We calibrate both the 1D and the 2D specifications of our framework. A subset of parameters is fixed at standard values: we set the annual discount rate to 0.05 and the utility curvature parameter, η, to 1.5.[55] We assume equal Nash-bargaining power, $\mu_m = 1 - \mu_f = 0.5$, and normalize the meeting rates λ_f and λ_m by fixing the scaling factor to $\bar{\lambda} = 1$.[56] We fix the annual relationship dissolution rate at $\delta = 0.06$ to match its empirical counterpart in the data. The remaining parameters are calibrated by minimizing the relative distance between theoretical and empirical moments. In the 1D model, we calibrate $\{\kappa_1, \kappa_2, \mu_z, \sigma_z\}$ to match four moments: the share of married individuals, the marriage rate (i.e., the flow into marriage), the cross-sectional correlation in matched partner's incomes, and the variance of log-household income.[57] In the 2D model, we calibrate $\{\omega_1, \omega_2, \mu_z, \sigma_z, \rho\}$, additionally targeting the effect of job displacement on

[53] To see this, note that the cross-partial derivative of the term is negative for $\eta > 0$, which implies a negative cross-partial derivative of the match flow value, $f(q_f, q_m) = u_f^1(q_f, q_m) + u_m^1(q_f, q_m)$. This is part of the sufficient conditions for negative assortative matching (NAM) derived in Shimer and Smith (2000).

[54] See, e.g., Gihleb and Lang (2016), who use a similar penalty term to capture homophily in marriage markets. Marimon and Zilibotti (2001) use a comparable notion to model suitability of workers for jobs.

[55] See, e.g., Attanasio, Low, and Sánchez-Marcos (2008).

[56] 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 scaling factor at $\lambda = 1$ implies the rate at which women and men meet potential partners is equal to the mass of singles of the opposite gender.

[57] A standard measure of income inequality, see, e.g., Blundell, Pistaferri, and Preston 2008.

rematching patterns, estimated in Section 4.4. Recall that $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m} = -0.25$ implies that among displaced men who rematch, a one-unit decline in own income is associated with matching with a partner with 0.25 units higher income. To compute the model analogue of $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m}$, we simulate an exogenous income shock and measure the average change in partner income among men who subsequently transition to new matches. All theoretical moments are computed in steady state. Empirical moments are computed in the estimation sample described in Section 3. Table B.4 summarizes all parameter values.

Model Fit Table 5 reports the model fit. Both the 1D and 2D versions of our framework match the targeted empirical moments closely. The key difference is that the 1D model fails to capture the observed rematching patterns following job displacement: it predicts a positive value for $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m}$, contrary to the empirical evidence. In contrast, the 2D model closely matches the estimated value of $\frac{\gamma_{\Delta q_f|R}}{\Delta q_m} = -0.25$. The inability of the 1D model to reconcile post-displacement rematching patterns with the cross-sectional correlation in partner incomes is in line with the theoretical results developed in Section 2.

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, Corr$(\text{income}_f, \text{income}_m)$	0.22	0.22	0.22
Income inequality, 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 main estimation sample described in Subsection 3.3.

Simulation Results We use the calibrated models to simulate an increase in individual income inequality by applying the following transformation to individual income, separately for men and women:[58]

$$\tilde{q} = \max\Big(c \cdot (q - \mu_{q,g}) + \mu_{q,g}, q_{\text{min}}\Big). \tag{13}$$

This transformation scales deviations from the gender-specific mean $\mu_{q,g}$, where c governs the degree of dispersion and q_{min} ensures that incomes remain strictly positive. In our simulations, we set $c = 1.15$ and $q_{min} = 5000$ DKK, resulting in a 23% increase in the variance of income for men and a 29% increase for women.

Table 6 reports between-household inequality under three scenarios: (1) the calibrated baseline, (2) the counterfactual with increased individual income inequality holding the sorting of individuals into couples fixed, and (3) the counterfactual allowing sorting to adjust. Comparing scenarios (1) and (3), the 1D

[58] In the 1D model, the transformation is applied to the scalar agent type, q_g, in the 2D model it is applied to the first component of type, q_{1g}, which captures income.

Table 6: Simulation Results: Income Inequality and Marital Sorting

	Var(log(income$_f$ + income$_m$))	
	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.

model predicts a substantially larger increase in between-household inequality than the 2D model. The comparison between scenarios (2) and (3) shows that this difference is driven by marriage market sorting. The 1D model, which is rejected by our empirical evidence, predicts that sorting on income amplifies the rise in inequality. In contrast, the 2D model predicts that marital sorting on income dampens it, consistent with negative sorting on income, as suggested by our findings. Quantitatively, under the counterfactual, the 2D model predicts 30% lower between-household income inequality (0.174) than the 1D model (0.250). These simulation results illustrate the differences between 1D models, which are inconsistent with our empirical evidence, and the 2D model, which aligns with our findings.[59]

7 Conclusion

Understanding marital sorting is key to analyzing inequality and assessing how marriage markets respond to wage structure or policy changes. In this paper, we leverage exogenous variation from establishment closures to provide new empirical evidence on marital sorting patterns. Our findings show that displaced men are more likely to separate from low-earning partners and rematch with higher-earning women relative to a non-displaced control group. We show within an equilibrium search framework of marriage and divorce that our empirical findings are difficult to reconcile with one-dimensional matching but consistent with multidimensional matching. In particular, our findings suggest that observed sorting patterns in income arise not only from sorting on income itself but also from sorting on other traits that correlate with income.

Our findings point to several directions for future work. One avenue is to leverage exogenous variation in characteristics other than income, such as health or education, to improve our understanding of the mechanisms underlying observed sorting patterns in these dimensions. Another open question is to what

[59]Note that our simulation results do not contradict an overall positive contribution of marital sorting to between-household inequality: positive sorting on non-income traits increases between-household inequality, although negative sorting on income dampens this effect to some extent. For example, in the 2D model, a rise in sorting on education over time can be captured by an increase in ω_2, which strengthens homophily on non-income traits. Since these traits are positively correlated with income in our calibration, this leads to a rising correlation between partners' incomes over time (a pattern documented, e.g., by Lise and Seitz 2011)

extent observed marital sorting patterns arise from complementarities in the marital match value, or from heterogeneity in meeting opportunities (e.g., due to geographic segregation as in Alonzo, Guner, and Luccioletti, 2023), or the context in which couples meet (e.g., at work or university, see Kirkebøen, Leuven, Mogstad, and Mountjoy, 2025). More broadly, our results highlight the value of combining structural modeling with quasi-exogenous variation to study the mechanisms that give rise to marital sorting.

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Appendix

A Proofs and Derivations

Definition of PAM and NAM: 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).[60]

Definition A1. *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.

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 τ, 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 τ, 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 δ. The overall probability that a man in the control group experiences a breakup from his t_0-partner between t_0 and τ is thus given by:

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

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 τ 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 $q_f(t_0) \in \mathcal{M}\left(q_m(t_0)\right)$ but $q_f(t_0) \notin \mathcal{M}\left(q_m(t_0) - d\right)$.

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 $q_m$und PAM and that are

[60] 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.

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 δ 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 τ is given by:

$$\begin{aligned} P\left(D_B = 1 | D = 1\right) \quad = \quad & \underbrace{1 - e^{-\delta(\tau - t_0)}}_{\text{prob. of exogenous breakups}} \\ & + \underbrace{\int G_f(b(q_m(t_0))) - G_f((\max\{b(q_m(t_0) - d), a(q_m(t_0))\}) dF(q_m(t_0)|D = 1)}_{\text{prob. of endogenous breakups}} . \end{aligned} \tag{A.2}$$

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 τ is:

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

From (A.1), (A.2), and (A.3) it follows that under PAM as well as under NAM
$\gamma_B = P\left(D_B = 1 | D = 1\right) - P\left(D_B = 1 | D = 0\right) \geq 0$. 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

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

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

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

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 compard 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.[61] 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 negative and bounded above by

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

Denote by D_δ an indicator that equals 1 for men who experience an exogenous breakup between t_0 and τ, 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 τ. The average female type this group of men is matched with in t_0 can be written as weighted average:

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

[61] 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 $\gamma_{R=0|B}$.

(A.5)

Next we turn to computing the corresponding average for period τ, 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 τ is:

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

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

$$\begin{aligned}
\mathbb{E}\left[q_f(t_0)|D_R=1, D_B=1, D=0, q_m(t_0)=q_m\right] &= \mathbb{E}\left[q_f(\tau)|D_R=1, D_B=1, D=0, q_m(t_0)=q_m\right] \\
&= \frac{1}{G_f(b(q_m)) - G_f(a(q_m))} \int\limits_{a(q_m)}^{b(q_m)} q_f dG_f(q_f) \\
&= \mathbb{E}\left[q_f|a(q_m) < q_f < b(q_m)\right]. \qquad \text{(A.7)}
\end{aligned}$$

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

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

$$
\begin{aligned}
&= -\int \int_0^d \frac{\partial \mathbb{E}\left[q_f|q_m\right]}{\partial q_m}\Big|_{q_m=q-x} dx dF(q|D_R=1, D_B=1, D=1) \\
&= \overline{\gamma}_{\Delta q_f|R},
\end{aligned}
$$

where the weak inequality follows as[62]

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

As shown by Shimer and Smith (2000), $\mathbb{E}\left[q_f|q_m\right]$ is weakly increasing in q_m under PAM, from which $\overline{\gamma}_{\Delta q_f|R} \leq 0$ 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 $\underline{\gamma}_{\Delta q_f|R} \geq 0$ (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 $\mathbb{E}\left[q_f|a(q_m) < q_f < b(q_m)\right]$ 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[63]

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

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

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

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

[63]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 $h(x)$.

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

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).[64]

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

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.,

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

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

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:

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

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 $\mathcal{M}_i(q'_{mi}, q_m^{-i}, q_f^{-i})$.

[64]Note that $\mathcal{M}_i$ is bounded, as it is a subset of $\left[\underline{q}_i, \overline{q}_i\right]$ by assumption.

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. □

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 τ, 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 δ. Like in the one-dimensional case, the probability that control group couples break up between t_0 and τ is thus given by

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

under PAM as well as under NAM.

In the treatment group, the *i*-th dimension of men's type changes between t_0 and τ 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 $q_f(t_0) \in \mathcal{M}\left((q_m^i, q_m^{-i})\right)$ and $q_f(t_0) \notin \mathcal{M}\left((q_m^i - d, q_m^{-i})\right)$. 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

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

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

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

Additionally, breakups occur exogenously at rate δ 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 τ is:

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

$$+\int\int G_{fi}\left(b_i(q_{mi},q_m^{-i},q_f^{-i})|q_f^{-i}\right)$$
$$-G_{fi}\left(\max\{b_i(q_{mi}-d,q_m^{-i},q_f^{-i}),a_i(q_{mi},q_m^{-i},q_f^{-i})\}|q_f^{-i}\right)dG_f^{-i}\left(q_f^{-i}\right)dF(q_m) \tag{A.14}$$

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

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

From (A.13), (A.14), and (A.15) it follows that under PAM(i) as well as under NAM(i) $\gamma_B = P\left(D_B=1|D=1\right) - P\left(D_B=1|D=0\right) \geq 0$, concluding the proof of statement *1*.

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

Denote by D_δ an indicator that equals 1 for men who experience an exogenous breakup between t_0 and τ, 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 τ. 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:

$$\mathbb{E}\left[q_{fi}(t_0)|D_R=1,D_B=1,D=1,q_m(t_0)=q_m,q_f^{-i}(t_0)=q_f^{-i}\right]=$$
$$\mathbb{E}\left[q_{fi}(t_0)|D_R=1,D_B=1,D=1,q_m,q_f^{-i},D_\delta=1\right]P(D_\delta=1|D_R=1,D_B=1,D=1,q_m,q_f^{-i})$$
$$+\mathbb{E}\left[q_{fi}(t_0)|D_R=1,D_B=1,D=1,q_m,q_f^{-i},D_\delta=0\right]P(D_\delta=0|D_R=1,D_B=1,D=1,q_m,q_f^{-i})$$
$$=\frac{1-e^{-\delta(\tau-t_0)}}{1-e^{-\delta(\tau-t_0)}+G_{fi}(b_i(q_{mi},q_m^{-i},q_f^{-i})|q_f^{-i})-G_{fi}(\max\{b_i(q_{mi}-d,q_m^{-i},q_f^{-i}),a_i(q_{mi},q_m^{-i},q_f^{-i})\}|q_f^{-i})}$$
$$\cdot\frac{1}{G_{fi}(b_i(q_{mi},q_m^{-i},q_f^{-i})|q_f^{-i})-G_{fi}(a_i(q_{mi},q_m^{-i},q_f^{-i})|q_f^{-i})}\int\limits_{a_i\left(q_{mi},q_m^{-i},q_f^{-i}\right)}^{b_i\left(q_{mi},q_m^{-i},q_f^{-i}\right)} q_{fi}dG_{fi}(q_{fi}|q_f^{-i})$$
$$+\frac{G_{fi}(b_i(q_{mi},q_m^{-i},q_f^{-i})|q_f^{-i})-G_{fi}(\max\{b_i(q_{mi}-d,q_m^{-i},q_f^{-i}),a_i(q_{mi},q_m^{-i},q_f^{-i})\}|q_f^{-i})}{1-e^{-\delta(\tau-t_0)}+G_{fi}(b_i(q_{mi},q_m^{-i},q_f^{-i})|q_f^{-i})-G_{fi}(\max\{b_i(q_{mi}-d,q_m^{-i},q_f^{-i}),a_i(q_{mi},q_m^{-i},q_f^{-i})\}|q_f^{-i})}$$
$$\cdot\frac{1}{G_{fi}(b_i(q_{mi},q_m^{-i},q_f^{-i})|q_f^{-i})-G_{fi}(\max\{b_i(q_{mi}-d,q_m^{-i},q_f^{-i}),a_i(q_{mi},q_m^{-i},q_f^{-i})\}|q_f^{-i})}$$

$$\int_{\max\{b_i(q_{mi}-d,q_m^{-i},q_f^{-i}),a_i(q_{mi},q_m^{-i},q_f^{-i})\}}^{b_i(q_{mi},q_m^{-i},q_f^{-i})} q_{fi} dG_{fi}(q_{fi}|q_f^{-i})$$

$$= \frac{1-e^{-\delta(\tau-t_0)}}{1-e^{-\delta(\tau-t_0)}+G_{fi}(b_i(q_{mi},q_m^{-i},q_f^{-i})|q_f^{-i})-G_{fi}(\max\{b_i(q_{mi}-d,q_m^{-i},q_f^{-i}),a_i(q_{mi},q_m^{-i},q_f^{-i})\}|q_f^{-i})}$$

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

$$+\frac{G_{fi}(b_i(q_{mi},q_m^{-i},q_f^{-i})|q_f^{-i})-G_{fi}(\max\{b_i(q_{mi}-d,q_m^{-i},q_f^{-i}),a_i(q_{mi},q_m^{-i},q_f^{-i})\}|q_f^{-i})}{1-e^{-\delta(\tau-t_0)}+G_{fi}(b_i(q_{mi},q_m^{-i},q_f^{-i})|q_f^{-i})-G_{fi}(\max\{b_i(q_{mi}-d,q_m^{-i},q_f^{-i}),a_i(q_{mi},q_m^{-i},q_f^{-i})\}|q_f^{-i})}$$

$$\cdot\mathbb{E}\left[q_{fi}|\max\{b_i(q_{mi}-d,q_m^{-i},q_f^{-i}),a_i(q_{mi},q_m^{-i},q_f^{-i})\}<q_{fi}<b_i(q_{mi},q_m^{-i},q_f^{-i}),q_f^{-i}\right] \tag{A.16}$$

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

$$\mathbb{E}\left[q_{fi}(\tau)|D_R=1,D_B=1,D=1,q_m,q_f^{-i}\right]$$

$$=\frac{1}{G_{fi}(b_i(q_{mi}-d,q_m^{-i},q_f^{-i}))-G_{fi}(a_i(q_{mi}-d,q_m^{-i},q_f^{-i}))}\int_{a_i\left(q_{mi}-d,q_m^{-i},q_f^{-i}\right)}^{b_i\left(q_{mi}-d,q_m^{-i},q_f^{-i}\right)} q_{fi}dG_{fi}(q_{fi}|q_f^{-i})$$

$$=\mathbb{E}\left[q_{fi}|a_i(q_{mi}-d,q_m^{-i},q_f^{-i})<q_{fi}<b_i(q_{mi}-d,q_m^{-i},q_f^{-i}),q_f^{-i}\right]. \tag{A.17}$$

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

$$\mathbb{E}\left[q_{fi}(t_0)|D_R=1,D_B=1,D=0,q_m,q_f^{-i}\right]$$

$$=\mathbb{E}\left[q_{fi}(\tau)|D_R=1,D_B=1,D=0,q_m,q_f^{-i}\right]$$

$$=\frac{1}{G_{fi}(b_i(q_{mi},q_m^{-i},q_f^{-i}))-G_{fi}(a_i(q_{mi},q_m^{-i},q_f^{-i}))}\int_{a_i\left(q_{mi},q_m^{-i},q_f^{-i}\right)}^{b_i\left(q_{mi},q_m^{-i},q_f^{-i}\right)} q_{fi}dG_{fi}(q_{fi}|q_f^{-i})$$

$$=\mathbb{E}\left[q_{fi}|a_i(q_{mi},q_m^{-i},q_f^{-i})<q_{fi}<b_i(q_{mi},q_m^{-i},q_f^{-i}),q_f^{-i}\right] \tag{A.18}$$

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

$$\begin{aligned}\gamma_{\Delta q_{fi}|R} \quad = \quad & \int \mathbb{E}\left[q_{fi}(\tau)-q_{fi}(t_0)|D_R=1,D_B=1,D=1,q_m,q_f^{-i}\right] dG_f^{-i}(q_f^{-i})dF(q_m|D_R=1,D_B=1,D=1)\\ & -\int \mathbb{E}\left[q_{fi}(\tau)-q_{fi}(t_0)|D_R=1,D_B=1,D=0,q_m,q_f^{-i}\right] dG_f^{-i}(q_f^{-i})dF(q_m|D_R=1,D_B=1,D=0)\end{aligned}$$

$$
\begin{aligned}
= & \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})} \\
& \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. \\
& \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) \\
& +\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})} \\
& \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. \\
& \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) \\
& dG_f^{-i}(q_f^{-i})dF(q_m|D_R=1,D_B=1,D=1) \\
\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. \\
& \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\left.\frac{\partial\mathbb{E}\left[q_{fi}|q_{mi},q_m^{-i},q_f^{-i}\right]}{\partial q_{mi}}\right|_{q_{mi}=q-x}dxdG_f^{-i}(q_f^{-i})dF(q|D_R=1,D_B=1,D=1) \\
= & \overline{\gamma}_{\Delta q_{fi}|R},
\end{aligned}
$$

where the weak inequality follows as

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

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 $\overline{\gamma}_{\Delta q_{fi}|R}\leq 0$ 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 $\overline{\gamma}_{\Delta q_{fi}|R}\geq 0$ (statements *4.-a* and *4.-b*). □

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}:

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

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, $(b_i(q_{mi}, q'_{mj}, q_m^{-i}, q_f^{-i}), q_f^{-i}) \in \mathcal{M}((q_{mi}, q'_{mj}, q_m^{-i,j}))$ 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

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

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 $\mathbb{E}\left[q_{fi}|q_{mi}, q_{mj}, q_{fj}\right]$. It follows that

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

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

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

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 $\mathbb{E}\left[q_{fi}|q_{mi}, q_{mj}, q_{fj}\right]$. It follows that

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

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. $\square$

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 $q''_{mi} \geq q'_{mi}$*

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

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

$$\begin{aligned}
PAM(i) \quad &\Rightarrow \quad DE \geq 0, \\
NAM(i) \quad &\Rightarrow \quad DE \leq 0
\end{aligned}$$

Given $PAM(j)$ for $j \in A_{PAM}$ and $NAM(j)$ for $j \in A_{NAM}$, where $A_{PAM} \cup A_{NAM} = \{1, ..., K\}$, the following additional implications hold.[65]

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

[65]Note that analogous sufficient conditions for $\text{IE}_k \geq 0$ and $\text{IE}_k \leq 0$ can be proved assuming in the antacedent that $G(q_{mk}|q_{m,k+1:K\setminus\{i\}}, q_{mi})$ is weakly increasing in q_{mi}. We ommit these additional implications for brevity.

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

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

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

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 $\mathbb{E}\left[q_{fi}|q_{mi},q_m^{-i},q_f^{-i}\right]$. It follows that

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

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

Note that IE_k can be expressed as

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

By Lemma 1

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

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 $j \in A_{\text{PAM}}$, and weakly decreasing in q_{mj} for all $j \in A_{\text{NAM}}$, implying the same for $\mathbb{E}[q_{fi}|q_{mi},q_m^{-i}]$.

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

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

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

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

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

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

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

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 toegether with (A.24) being weakly increasing in q_{mk} that

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

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 and Figures

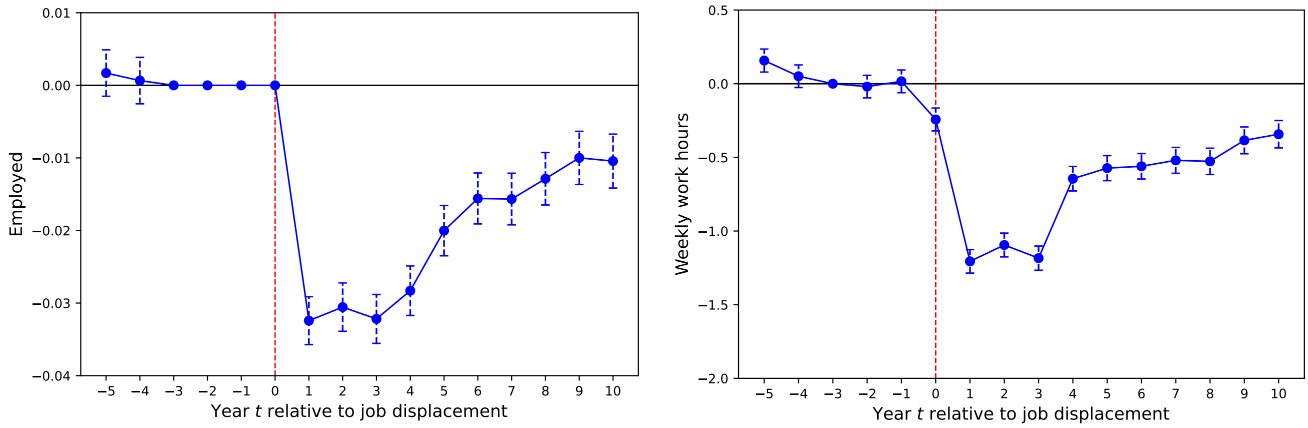
Table B.1: Pre-displacement Summary Statistics, Treatment and Control Group

	Treatment	Control
Age	38.1	38.1
	(36.2)	(36.2)
Partner's age	36.2	36.2
	(12.6)	(12.6)
Years of education	12.6	12.6
	(2.4)	(2.4)
Patner's years of education	12.2	12.3
	(2.4)	(2.4)
Job tenure	6.4	6.4
	(4.1)	(4.0)
No. of children	1.5	1.5
	(1.0)	(1.0)
Labor income (in DKK)	326,247	324,898
	(97021)	(96761)
Partner's labor income (in DKK)	177,682	178,891
	(106798)	(106877)
$\text{Corr}(\text{age}_f, \text{age}_m)$	0.83	0.83
$\text{Corr}(\text{education}_f, \text{education}_m)$	0.38	0.39
$\text{Corr}(\text{income}_f, \text{income}_m)$	0.15	0.15
N	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).

Figure B.1: Labor Market Outcomes of Displaced Men:
Employment and Weekly Work Hours

(A) Employment (B) Weekly Work Hours



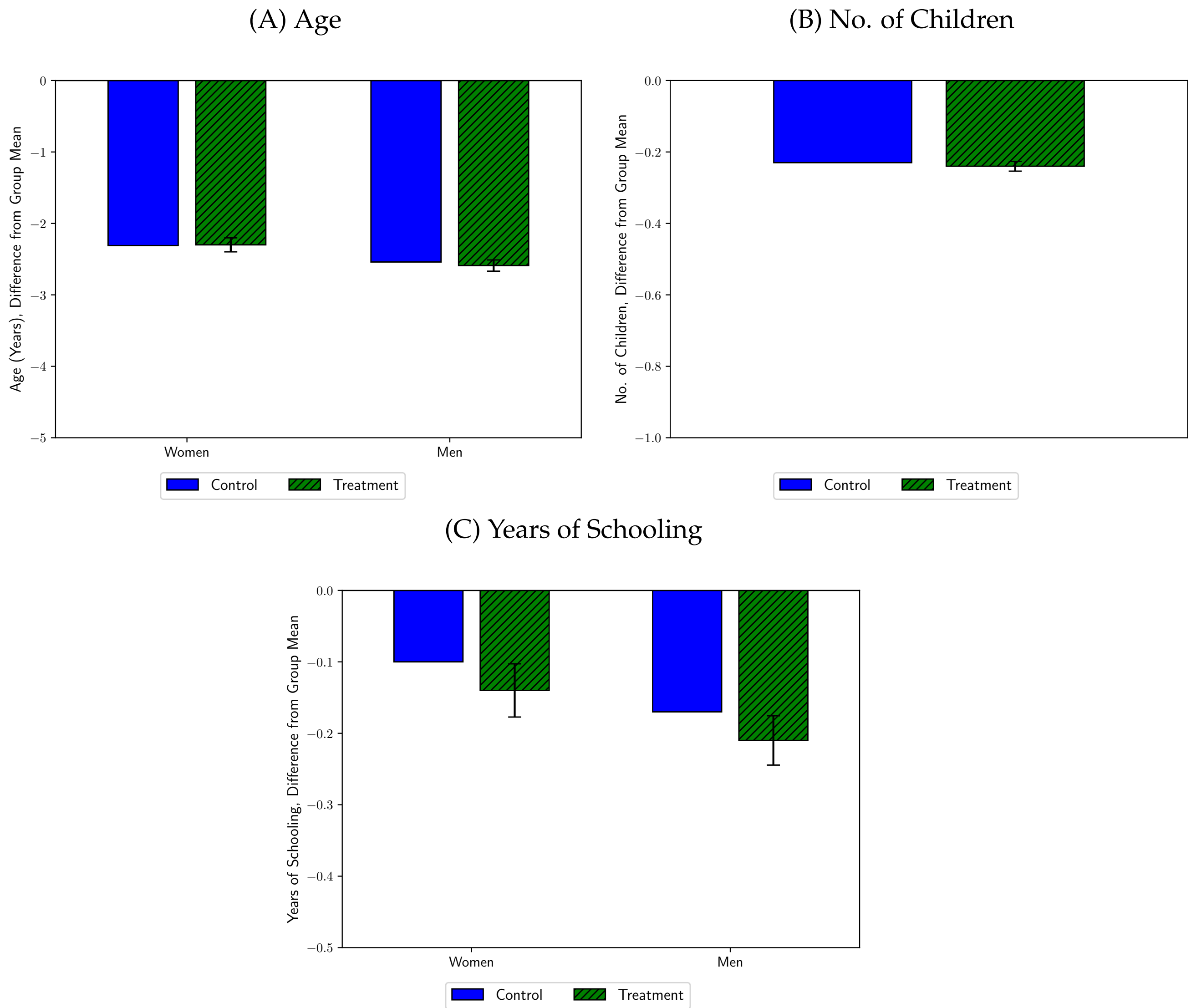
<u>Notes:</u> The figure shows the impact of job displacement on employment (Panel A) and weekly work hours (Panel B). Dashed vertical lines around each point estimate represent 95% confidence intervals. The estimates correspond to ϕ_τ from Equation (8). All results are based on a sample of men displaced due to establishment closures between 1980 and 2007, and a matched control group selected via coarsened exact matching. Sample selection criteria and the matching algorithm are described in Subsection 3.3.

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

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

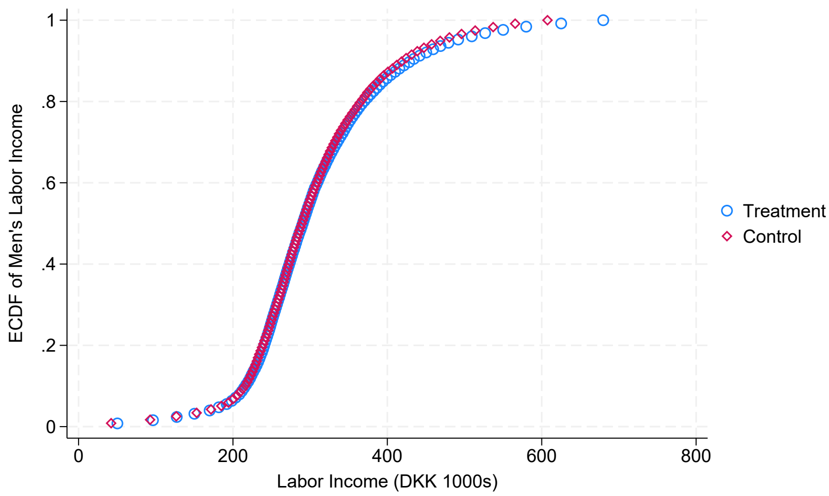
<u>Notes</u>: This table reports the effect of men's job displacement on two outcomes: (i) the probability of being matched with a partner in period $t+1$, conditional on having been single in period t (column 1); and (ii) the probability of being matched with a partner at some point $t > t^*$, after having been single in at least one period $t^* > -3$ (column 2). All estimates are based on a sample of men who experienced an establishment closure between 1980 and 2007 and an equally sized control group selected by exact matching. Sample selection criteria and matching procedures are described in Subsection 3.3. Standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure B.2: Pre-Displacement Age, Education and No. of Children of Couples Who Break Up



Notes: The figure displays the pre-displacement characteristics of women and men who experience a breakup. Panel A shows average age, Panel B shows the average number of children, and Panel C shows average years of schooling in $t \in \{-5, \dots, -3\}$ (before the male partner's actual or placebo displacement) for individuals who separate between $t = 0$ and $t = 10$ (after the male partner's actual or placebo displacement). All values are normalized by the respective sample average. The underlying sample includes men who were displaced as part of an establishment closure between 1980 and 2007, and an equally sized control group selected by coarsened exact matching. The specific sample selection criteria and matched sampling algorithm are described in Subsection 3.3.

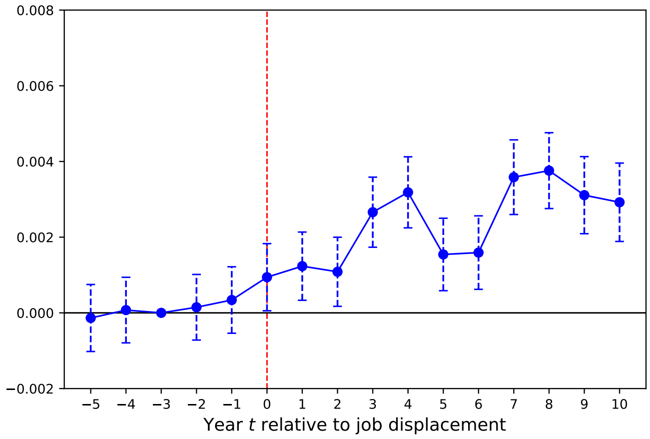
Figure B.3: Pre-Displacement Income of Couples Who Break Up:
Empirical CDFs of Men's Labor Income



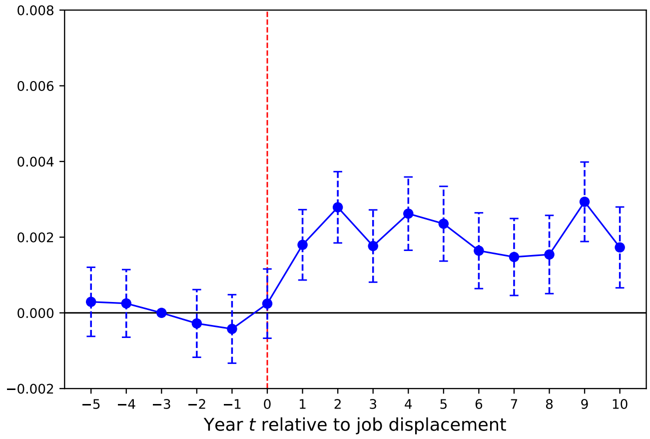
Notes: The figure displays the pre-displacement labor income distribution of men who experience a breakup. The plotted empirical CDFs are based on pre-displacement labor income in $t \in \{-5, \ldots, -3\}$ (before the male partner's actual or placebo displacement) for individuals who experience a breakup between $t = 0$ and $t = 10$ (after the male partner's actual or placebo displacement). Each dot in the plot represents an average across 100 individuals, aggregated to comply with Statistics Denmark's data confidentiality policy. The underlying sample includes men who were displaced as part of an establishment closure between 1980 and 2007, and an equally sized control group selected by coarsened exact matching. The specific sample selection criteria and matched sampling algorithm are described in Subsection 3.3.

Figure B.4: Rematching Patterns of Displaced Men:
New Partners' vs. Old Partners' Income

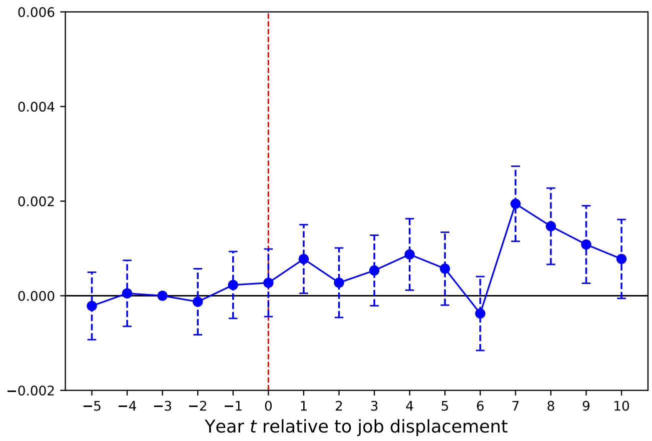
(A) New Partner's Income $\geq 10\%$ Higher than $t = -3$ Partner's Income



(B) New Partner's Income in $\pm 10\%$ Range of $t = -3$ Partner's Income



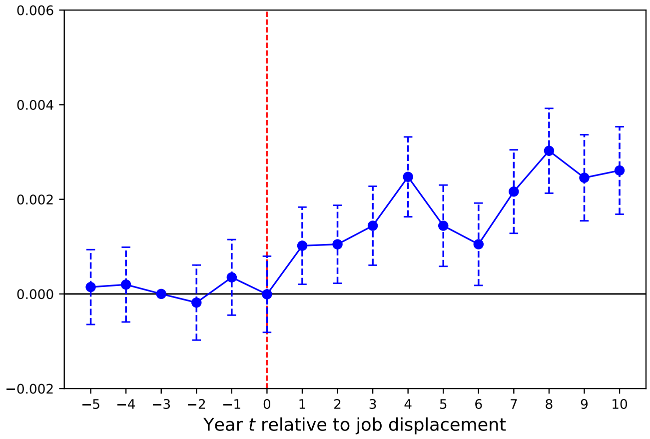
(C) New Partner's Income at least 10% Lower than $t = -3$ Partner's Income



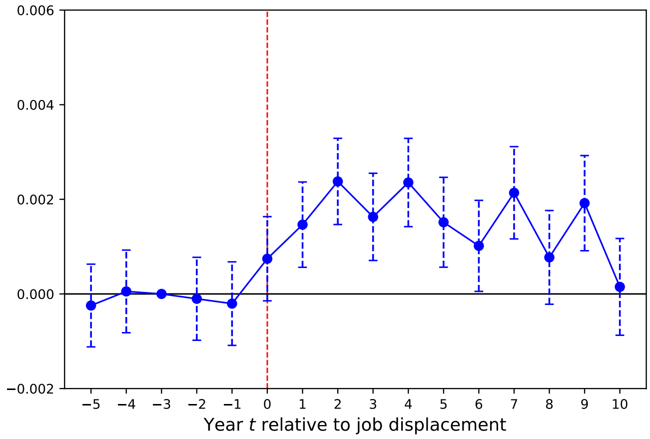
Notes: The figure shows the effect of job displacement on the rematching patterns of men after a breakup. Panel A displays the effect on the probability of matching with a new partner with at least 10% higher labor income than that of the pre-displacement partner (defined as the partner at $t = -3$). Panel B shows the effect on the probability of matching with a new partner with labor income between –10% and +10% of the pre-displacement partner's labor income. Panel C shows the effect on the probability of matching with a new partner with at least 10% lower labor income than that of the pre-displacement partner. The estimates correspond to ϕ_τ from Equation (8). Dashed vertical lines around point estimates indicate 95% confidence intervals. All estimates are based on a sample of men displaced due to establishment closures between 1980 and 2007 and a control group selected by coarsened exact matching. Sample selection and matching procedures are detailed in Subsection 3.3.

Figure B.5: Rematching Patterns of Displaced Men:
New Partners' vs. Old Partners' Hourly Wage

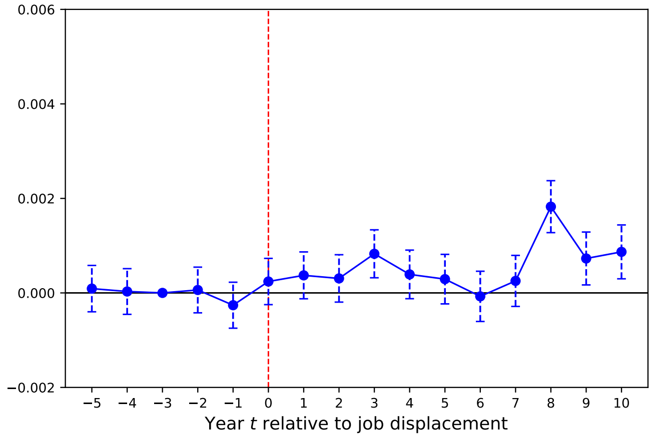
(A) New Partner's Hourly Wage $\geq 5\%$ Higher than $t = -3$ Partner's Hourly Wage



(B) New Partner's Hourly Wage in $\pm 5\%$ Range of $t = -3$ Partner's Hourly Wage



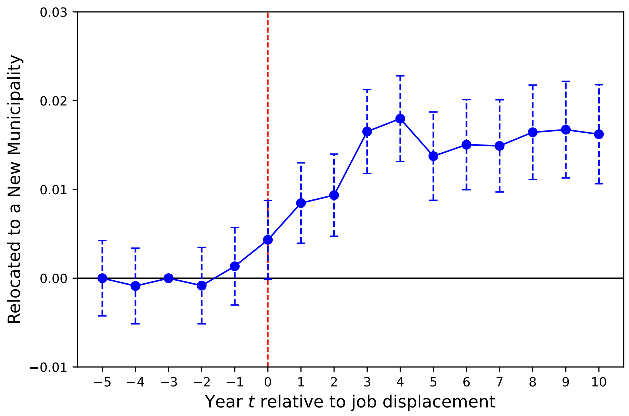
(C) New Partner's Hourly Wage at least 5% Lower than $t = -3$ Partner's Hourly Wage



Notes: The figure shows the effect of job displacement on the rematching patterns of men after a breakup. Panel A displays the effect on the probability of matching with a new partner with at least 5% higher hourly wage than that of the pre-displacement partner (defined as the partner at $t = -3$). Panel B shows the effect on the probability of matching with a new partner with hourly wage between –5% and +5% of the pre-displacement partner's hourly wage. Panel C shows the effect on the probability of matching with a new partner with at least 5% lower hourly wage than that of the pre-displacement partner. The estimates correspond to ϕ_τ from Equation (8). Dashed vertical lines around point estimates indicate 95% confidence intervals. All estimates are based on a sample of men displaced due to establishment closures between 1980 and 2007 and a control group selected by coarsened exact matching. Sample selection and matching procedures are detailed in Subsection 3.3.

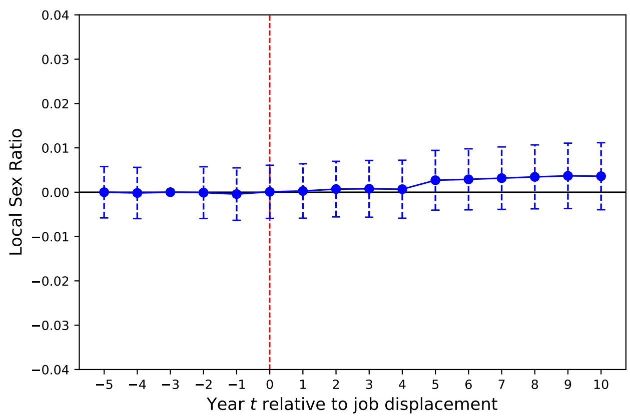
Figure B.6: Robustness Checks

(A) Relocations to a New Municipality



(B) Earnings of Single Women in Location of Residence

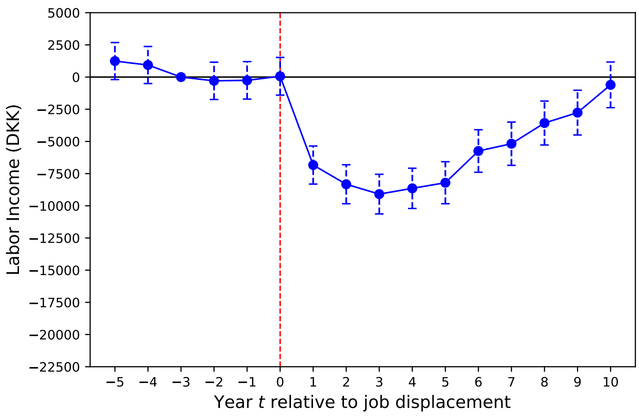
(C) Sex Ratio in Location of Residence



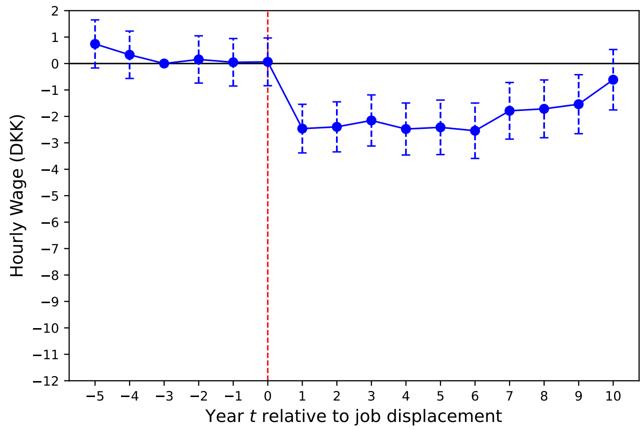
Notes: Panel A shows the effect of men's job displacement on the probability of moving to a different municipality. Panel B displays the difference in average annual labor income of single women between the municipalities where displaced and control men reside in period t. Panel C shows the difference in the sex ratio $\left(\frac{\text{\# single women}}{\text{\# single men}}\right)$ between the municipalities where displaced and control men reside in period t. The estimates correspond to ϕ_τ from Equation (8). All estimates are based on a sample of men who experienced an establishment closure between 1980 and 2007 and an equally sized control group selected by exact matching. Sample selection criteria and matching procedures are described in Subsection 3.3.

Figure B.7: Labor Market Outcomes of Displaced Women

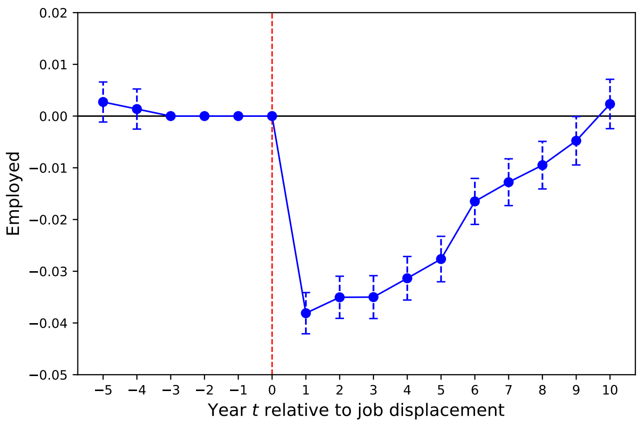
(A) Labor Income (in DKK)



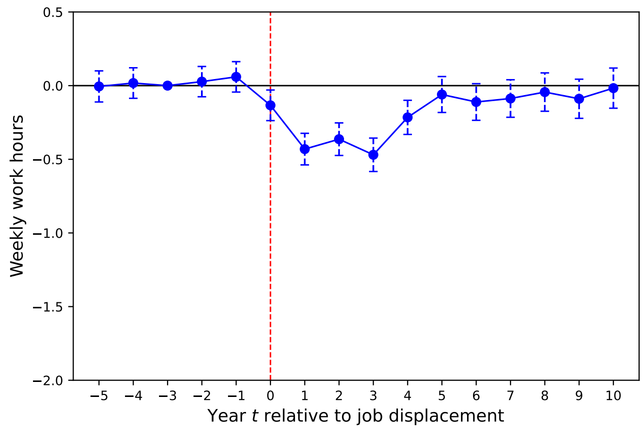
(B) Hourly Wage (in DKK)



(C) Employment



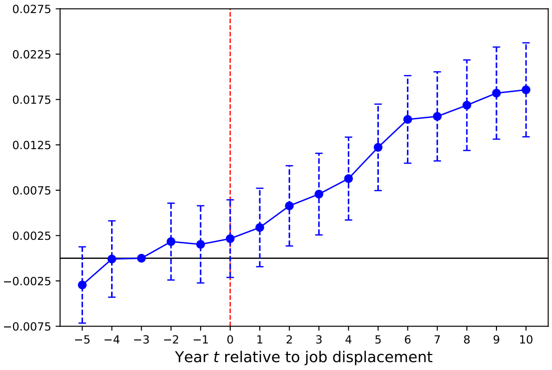
(D) Weekly Work Hours



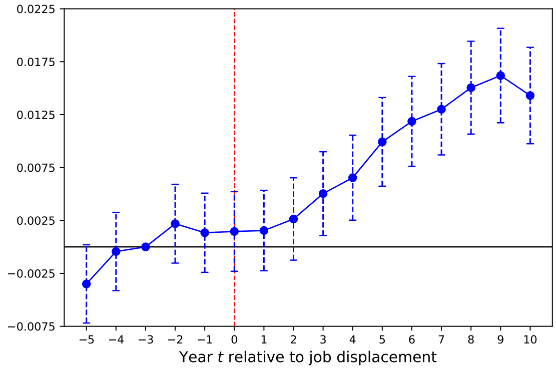
Notes: The figure shows the impact of job displacement on annual labor income (Panel A), hourly wages (Panel B), employment (Panel C) and weekly work hours (Panel D). Labor income includes zeros for nonemployed individuals, while hourly wages are conditional on employment. Labor outcomes and hourly wages are measured in DKK (CPI 2004). Dashed vertical lines around each point estimate represent 95% confidence intervals. The estimates correspond to ϕ_τ from Equation (8). All results are based on a sample of women displaced due to establishment closures between 1980 and 2007, and a matched control group selected via coarsened exact matching. The sample selection criteria and matching algorithm are analogous to those used for displaced men, which are described in Subsection 3.3.

Figure B.8: Relationship Status and Rematching Patterns of Displaced Women

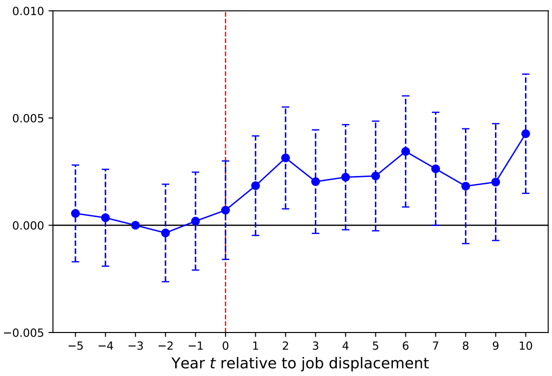
(A) Separated



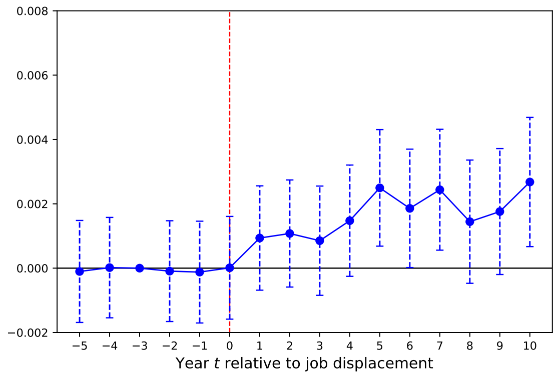
(B) Single



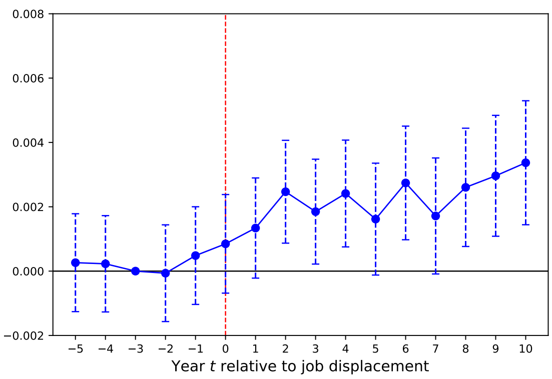
(C) New Partner



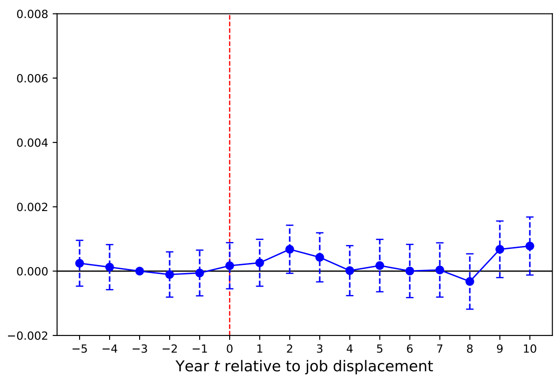
(D) New Partner's Income $\geq 5\%$ Higher than $t = -3$ Partner's Income



(E) New Partner's Income in $\pm 5\%$ Range of $t = -3$ Partner's Income



(F) New Partner's Income at least 5% Lower than $t = -3$ Partner's income



Notes: Panels A–C show the effects of women's job displacement on their relationship status. Panel A displays the effect on the probability of being separated from the pre-displacement partner, defined as the partner at $t = -3$. Panel B shows the effect on the probability of being single, and Panel C shows the effect on the probability of being married or cohabiting with a new partner. Panels D-F shows the effect of women's job displacement on the rematching patterns of women after a breakup. Panel D displays the effect on the probability of matching with a new partner with at least 5% higher labor income than that of the pre-displacement partner (defined as the partner at $t = -3$). Panel E shows the effect on the probability of matching with a new partner with labor income between –5% and +5% of the pre-displacement partner's labor income. Panel F shows the effect on the probability of matching with a new partner with at least 5% lower labor income than that of the pre-displacement partner. All displayed values correspond to coefficient estimates of ϕ_τ from Equation (8). Dashed vertical lines around point estimates indicate 95% confidence intervals. All results are based on a sample of women displaced due to establishment closures between 1980 and 2007, and a matched control group. The sample selection criteria and matching algorithm are analogous to those used for displaced men.

Table B.3: Rematching Patterns of Displaced Women:
New Partners' Income, Wage, and Work Hours

	Labor Income	Wage	Work Hours
Treated $\times$ post-displacement, γ	2301.23	1.03	0.09
	(2342.14)	(1.61)	(0.17)
No. of observations	68,908	44,112	39,660

Notes: The table shows the effect of women's job displacement on the types of partners they transition to, measured by partners' labor income, hourly wage (conditional on employment), and weekly work hours (including zeros for non-employed individuals). The table reports coefficient estimates of γ from Equation (9). Standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Calibrated Parameter Values

Parameter	Symbol	1D Model	2D Model	Comment
Discount rate	r	0.05	0.05	fixed
Risk aversion	η	1.5	1.5	fixed
Bargaining power	μ_f	0.50	0.50	fixed
Separation rate	δ	0.06	0.06	data estimate
Meeting rate scaling factor	$\bar{\lambda}$	1.00	1.00	fixed
Love shock mean	μ_z	7963.97	91768.12	calibrated
Love shock standard deviation	σ_z	3034.07	44.07	calibrated
Income NAM utility parameter 1D	κ_1	0.79	–	calibrated
Income PAM utility parameter 1D	κ_2	0.34	–	calibrated
Income NAM utility parameter 2D	ω_1	–	13844.73	calibrated
Unobserved PAM utility parameter 2D	ω_2	–	7724811.39	calibrated
Correlation Income/Unobserved dimension	ρ	–	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 Model Appendix

C.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

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

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

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

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:

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

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

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

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

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

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

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

C.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:

$Q_f = Q_m = \prod_{k=1}^{K} \left[\underline{q}_k, \overline{q}_k\right]$, 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, $\int L_m(q_m)\mathrm{d}q_m = 1$ and $\int L_f(q_f)\mathrm{d}q_f = 1$. 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 $\mathcal{G}_m = \int g_m(q_m)\mathrm{d}q_m$ and $\mathcal{G}_f = \int g_f(q_f)\mathrm{d}q_f$. We denote the endogenous bivariate PDF of married individuals by $c(q_m, q_f)$, and the mass of married couples by $\mathcal{C} = \iint c(q_m, q_f)\mathrm{d}q_m\mathrm{d}q_f$. These definitions imply that $l_m(q_m) = \int c(q_m, q_f)\mathrm{d}q_f + g_m(q_m)$ and $l_f(q_f) = \int c(q_m, q_f)\mathrm{d}q_m + g_f(q_f)$.

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

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:

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

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

$$\delta \int c(q_m, q_f)\mathrm{d}q_f = \bar{\lambda}g_m(q_m) \int g_f(q_f)\alpha(q_m, q_f)\mathrm{d}q_f. \tag{D.9}$$

Substituting $l_m(q_m) - g_m(q_m) = \int c(q_m, q_f)\mathrm{d}q_f$ yields:

$$\delta\left(l_m(q_m) - g_m(q_m)\right) = \bar{\lambda}g_m(q_m) \int g_f(q_f)\alpha(q_m, q_f)\mathrm{d}q_f, \tag{D.10}$$

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

$$g_m(q_m) = \frac{\delta l_m(q_m)}{\delta + \bar{\lambda} \int g_f(q_f)\alpha(q_m, q_f)\mathrm{d}q_f}. \tag{D.11}$$

Similarly, for women of type q_f:

$$g_f(q_f) = \frac{\delta l_f(q_f)}{\delta + \bar{\lambda} \int g_m(q_m)\alpha(q_m, q_f)\mathrm{d}q_m}. \tag{D.12}$$

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):

$$rV_m^0(q_m) = u_m^0(q_m) + \lambda_m \iint \max\{S_m(q_f, q_m), 0\}\mathrm{d}F_z(z)\frac{g_f(q_f)}{\mathcal{G}_f}\mathrm{d}q_f, \tag{D.13}$$

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

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

implying for $S_m(q_f, q_m)$:

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

Next, we use $\bar{\lambda} = \frac{\lambda_m}{\mathcal{G}_f}$ 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:

$$rV_m^0(q_m) = u_m^0(q_m) + \frac{\bar{\lambda}}{r + \delta} \iint \max\{\tilde{u}_m^1(q_f, q_m) + z + t_m - rV_m^0(q_m), 0\}\mathrm{d}F_z(z)g_f(q_f)\mathrm{d}q_f, \tag{D.16}$$

where the transfers, t_m, are given by

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

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

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

$$
\begin{aligned}
&+ \quad \frac{\bar{\lambda}(1-\mu_f)}{r+\delta}\iint \max\{2z+\tilde{u}^1_m(q_f,q_m)+\tilde{u}^1_f(q_f,q_m)\\
&- \quad rV^0_m(q_m)-rV^0_f(q_f),0\}\mathrm{d}F_z(z)g_f(q_f)\mathrm{d}q_f,
\end{aligned}
$$

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

$$
\begin{aligned}
rV^0_f(q_f) \quad &= \quad u^0_f(q_f) \\
&+ \quad \frac{\bar{\lambda}\mu_f}{r+\delta}\iint \max\{2z+\tilde{u}^1_m(q_f,q_m)+\tilde{u}^1_f(q_f,q_m)\\
&- \quad rV^0_m(q_m)-rV^0_f(q_f),0\}\mathrm{d}F_z(z)g_m(q_m)\mathrm{d}q_m.
\end{aligned} \tag{D.19}
$$

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.[66] 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 ρ. We calibrate ρ 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.

[66]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.