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Who partners up? Educational assortative matching and the distribution of income in New Zealand

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Abstract

Educational assortative matching among couples, i.e. the phenomenon whereby the high-educated have partners who are also high-educated, has gained attention in popular media and academic research as a driver of recent changes in the distribution of household income. We examine the effect of educational assortative matching on the distribution of household income in New Zealand - a country which has experienced rising inequality, increased educational attainment and a relatively low, and falling, wage premium for higher levels of education. Using data from the 1986, 1991, 1996, 2001, 2006 and 2013 Census of Population and Dwellings and a counterfactual randomisation methodology that accounts for secular changes in the educational distribution, we find that educational assortative matching has increased but, contrary to some evidence overseas, this increase was driven by increased matching in the middle of the educational distribution. Spatially, we find higher and increasing levels of educational assortative matching in metropolitan areas compared to non-metropolitan areas where assortative matching was lower and decreasing. We find that educational assortative matching has had an inequality-increasing impact on the distribution of income, especially for the full-time employed – for whom the matching impact is around 20 percent of the Mean Log Deviation measure of inequality. Additionally, sorting on observable characteristics such as age and location (with the higher educated being disproportionally attracted to the metropolitan areas) are also inequality-increasing and sorting on unobservable characteristics that impact on income can play an important role as well.

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D31, J12 and R23.

Keywords

Assortative matching, inequality

Summary haiku

Falling in love with
one as educated boosts
inequality.

Table of Contents

1 Introduction 5

2 Literature Review 9

3 Data and Methodology 13

3.1 Data 13

3.2 Methodology 15

4 Results: Educational Assortative Matching and Income Inequality in New Zealand 17

4.1 Patterns and changes in the personal income distribution for individuals participating in the labour force 17

4.2 Patterns and changes in the distribution of income of male-female couples working full-time 18

4.3 Patterns of educational assortative matching among male-female couples in New Zealand 21

4.4 The impact of assortative matching on income inequality among couples working full-time in New Zealand 34

5 Conclusion 41

References 43

Appendix 46

Recent Motu Working Papers 69

Tables and Figures

Figure 1: Assortative matching index for couples with same category of education by area in all periods 32

Figure 2: Effect of educational assortative matching on the distribution of income of couples working full-time in each Census period by area: MLDs 36

Table 1: Decomposition of personal income inequality (MLD) by labour-force groups: All urban areas combined 18

Table 2: Mean and inequality statistics by couple type in each census period for all urban areas combined 20

Table 3: Inequality of total income of male-female couples working full-time and aged 25-64 from 1986 to 2013 21

Table 4: Educational distribution for individuals in couples aged 25-64 in all urban areas from 1986 to 2013 22

Table 5: Actual proportion of couples in each educational pairing from 1986 to 2013: All urban areas combined 23

Table 6: Proportion of couples in each educational pairing from 1986 to 2013 under randomisation: All urban areas combined 24

Table 7: Concentration ratio: All urban areas combined 26

Table 8: Assortative matching index by educational group: All urban areas combined 29

Table 9: Assortative matching index by educational group for all areas 31

Table 10: Assortative matching index of occupational pairings of couples from 1986 to 2013 by area 33

Table 11: Effect of educational assortative matching on the distribution of income of couples working full-time in each Census period by area: MLDs 35

Table 12: Effect of educational assortative matching on the distribution of income of couples working full-time and everyone in the labour force Ginis and MLD 37

Table 13: Effect of educational assortative matching on the distribution of income of couples working full-time under unconditional and conditional randomisations using MLDs by area 39

Appendix Table A: Summary of MLD changes by area for the individual population 25-64. Source: Alimi et al. (2018) 46

Appendix Table B: Decomposition of personal income inequality by labour-force groups: Non-metropolitan areas 46

Appendix Table C: Decomposition of personal income inequality by labour-force groups: Metropolitan areas 47

Appendix Table D: Mean and inequality statistics by couple type in each census period for Non-metropolitan areas 48

Appendix Table E: Mean and inequality statistics by couple type in each census period for Metropolitan areas 49

Appendix Table F: Educational distribution for individuals in couples aged 25-64 in Non-metropolitan areas from 1986 to 2013 50

Appendix Table G: Educational distribution for individuals in couples aged 25-64 in Metropolitan areas from 1986 to 2013 51

Appendix Table H: Actual proportion of couples in each educational pairing: Non-metropolitan areas 52

Appendix Table I: Proportion of couples in each educational pairing under randomisation: Non-metropolitan areas 53

Appendix Table J: Actual proportion of couples in each educational pairing: Metropolitan areas 54

Appendix Table K: Proportion of couples in each educational pairing under randomisation: Metropolitan areas 55

Appendix Table L: Concentration ratio from 1986 to 2013: Non-metropolitan areas 56

Appendix Table M: Concentration ratio from 1986 to 2013: Metropolitan areas 57

Appendix Table N: Assortative matching index by educational group for non-metropolitan areas 58

Appendix Table O: Assortative matching index by educational group for metropolitan areas 59

Appendix Table P: Actual occupational pairings in 1986 and 2013: All urban areas 60

Appendix Table Q: Occupational pairing under randomisation in 1986 and 2013: All urban areas 61

Appendix Table R: Actual occupational pairings in 1986 and 2013: Non-metropolitan areas 62

Appendix Table S: Occupational pairing under randomisation in 1986 and 2013: Non-metropolitan areas 63

Appendix Table T: Actual occupational pairings in 1986 and 2013: Metropolitan areas 64

Appendix Table U: Occupational pairing under randomisation in 1986 and 2013: Metropolitan areas 65

Appendix Table V: Assortative matching index of occupational pairings for 1986 and 2013 in all urban areas 66

Appendix Table W: Assortative matching index of occupational pairings for 1986 and 2013 in non-metropolitan areas 67

Appendix Table X: Assortative matching index of occupational pairings for 1986 and 2013 in Metropolitan areas 68

1 Introduction

Changes in the distribution of income continue to be of concern in New Zealand[1]. At the household level, inequality rose rapidly in the mid-1980s and 1990s but stabilised at this higher level in the 2000s (Perry, 2017, Easton, 2013, Ball and Creedy, 2016). As for the rest of the developed world that has experienced growing income inequality since the 1980s, there is a large literature on explaining these distributional changes. Most of the attention has been on the role of economic drivers like sectoral shifts, pay at the top, globalisation and skill-biased technological change (Autor, Levy & Murnane, 2003, Michaels, Natraj & Van Reenen, 2014, Blum, 2008 and Henze, 2014). As well as the economic factors, there is also growing evidence that socio-demographic changes like ageing, migration and changes in the patterns of family formation have played a non-negligible role in influencing the distribution of income as well (see OECD, 2008 for a review of the international evidence; and Ball and Creedy, 2016 and Hyslop and Maré, 2005 for New Zealand evidence). One important socio-demographic mechanism that received considerable attention overseas but less so in New Zealand is the role of educational assortative matching of couples in driving household inequality[2]. Broadly defined, assortative matching is the selection of partners based on how similar they are with respect to certain characteristics. Traditionally, the pattern of partnering has been selective on characteristics such as age and ethnicity. Educational assortative matching is the partnering of people with similar educational levels. Since education is often a significant predictor of income, patterns of partnering and changes to these patterns may influence the distribution of income at the family or household level. In academic as well as popular media[3], the increasing sorting of couples into educationally homogenous relationships has been touted as a strong driver of growing inequality in the distribution of income at the household/family level. The argument goes as follows: education is typically a significant predictor of income; hence if people with similar levels of education increasingly partner up, this will lead to an increase in inter-household inequality driven by the gap that is created between the high-educated high-income households and the low-educated low-income households. Thus, reduction in intra-household inequality may be increasing inter-household inequality.

The study of assortative matching and its effect on the distribution of income is important because the process of partnering not only holds implications for cross-sectional inequality but is important for the future of inequality as well. If couples are sorting on characteristics that are increasingly correlated with income, this will affect the current distribution of income as well as

[1] See Collins (2014) and Edwards (2017).
[2] The descriptive studies by Callister and Didham (2010, 2014) are an exception.
[3] For popular media, see the Cowen (2015) article in the *New York Times* and the Worstall (2015) article in the *Forbes* magazine. The next section reviews the academic literature.

influence the inter-generational transmission of inequality, depending on how resources are passed down on to the next generation and the extent to which any form of observable or unobservable advantage is conferred on offspring. For example, Schwartz (2013) argues that when both partners of a couple are high-educated, this is positively related to child outcomes. Ermisch, Francesconi and Siedler (2006) use German and British data to show that on average about 40–50 percent of the covariance between parents' income and own family income can be attributed to the person to whom one is married. In New Zealand, Maré and Stillman (2010) provide evidence that children with more highly educated parents do better on cognitive tests. Assortative matching may not only have consequences for the current generation but also belongs to the category of structural change factors that may lead to, and perpetuate, permanent differences.

Intuitively, the role of assortative matching on the household income distribution seems direct but identifying the effect of assortative matching on the distribution of income is trickier due to the presence of many confounding factors[4]. Earlier studies took as evidence of educational assortative matching one or some of the following: changes in the correlation of educational attainment between couples, changes in the correlation of earnings between couples, and changes in the proportion of couples with the same level of education/earnings. However, this approach is flawed because secular trends like changes in the educational distribution can increase the correlation in couples' education or the proportion of couples with the same level of education, while increased labour force participation rates of women can influence the correlation between couples' earnings. As well as these secular trends that can confound the identification of the effect of assortative matching, another issue in the analysis of the effect of assortative matching on the distribution of income is the issue of joint labour supply responses. Couples typically make joint decisions to participate in the labour force. Incomes are determined not only by education level (as a proxy for earning potential) but also by hours worked. The individual decision on hours worked may be influenced by the income or education level of a partner. Thus, a high-earning high-educated person partnered to another high-earning-high-educated person may decide to work less. An example is a doctor who partnered another doctor and then works fewer hours than if partnered to a teacher. These secular trends and labour supply responses will affect estimates of educational assortative matching on the income distribution if they are not explicitly accounted for.

In this study, we analyse the trends and changes in the patterns of education assortative matching in New Zealand using individual unit record data from each Census from 1986 to 2013[5]. This period is particularly interesting because both inequality and the proportion of

[4] See Eika, Mogstad and Zafar (2014) for a review of factors that can confound the measure of assortative matching and Pestel (2017) for an explanation of how endogenous labour supply responses influence estimates of assortative matching.

[5] New Zealand Censuses were held in 1986, 1991, 1996, 2001, 2006, and 2013.

couples living in educationally homogenous households increased. In addition, there was a large increase in average educational attainment, decline in the gender pay gap, and increases in the labour force participation of females over this period. This study makes four important contributions: first, to the best of our knowledge, it is the first study to formally examine the effect of assortative matching on the distribution of income in New Zealand. While there is descriptive evidence in New Zealand of growing assortative matching (see Callister and Didham, 2010, 2014), its impact on household inequality has not been examined. In the last three or so decades, New Zealand has shared similarities with the US and some European countries in terms of growing inequality and changes in the educational distribution. However, New Zealand has a lower educational/skill premium and there is recent evidence that this premium has declined further[6]. We provide evidence on the role of assortative matching on the distribution of income in this interesting and unique context. Secondly, we take a spatial approach which is unique in the extant literature. Typically, studies of assortative matching are at the national level but one important mechanism for inequality at the sub-national level could be the inter-relationship between city size, assortative matching and household income. Because bigger cities attract more people, especially educated people in their prime ages, it is expected that there may be more assortative matching in bigger cities[7]. These patterns may translate to higher inequality in metropolitan areas and differences in rates of assortative matching may explain some of the variation in inequality across space already documented in New Zealand[8]. Thirdly, we show that concentration ratios (ratio of actual matching to random matching) which is very popular in the literature to describe changes in assortative matching are influenced by population proportions. This may lead to wrong conclusions on the patterns and trends of assortative matching. We present a new index that overcomes the limitation of the concentration ratios. Finally, past research on the impact of assortative matching on household inequality has been imperfect due to ignoring the confounding effect of endogenous joint labour supply responses and secular changes in the educational distribution not being taken into account. Through a counterfactual randomisation methodology, we address the changing educational distribution issue and by focusing on couples working full-time, we try to limit the possibility of joint labour supply responses[9]. This means that our results reflect the best available direct evidence on the effect of educational assortative matching on the distribution of income in New Zealand.

Our results will also have implications for policies meant to address inequality. If significant differences in inequality across areas are driven by what is happening in the patterns

6 See Zuccollo, Maani, Kaye-Blake and Zeng (2013) for OECD comparison of skill premiums and Maré (2018) for evidence on trends of the New Zealand skill premium.
7 In addition, in New Zealand, all eight universities, which may function as a "meet market", are in the largest urban areas.
8 See Karagedikli, Maré and Poot (2000, 2003) and Alimi, Maré and Poot (2016, 2017).
9 Even among full time workers, there is still the possibility of interacting labour supply responses of partners in terms of hours worked or choice of occupation. Some studies have adopted formal techniques to model these endogenous labour supply responses. For example, see Pestel (2017).

of matching, then we might want to revise our expectations of the capability of government policies to address inequality, unless of course the government is somehow given the means to intervene in the partnering market, which is extremely unlikely in a liberal and democratic society. Instead, policy is more likely to be aiming at enhancing geographic labour mobility to the extent that immobility imposes an economic disadvantage. In this study, we therefore examine assortative matching across space and focus on differences between metropolitan and non-metropolitan areas in partnering and its effect on the distribution of income.

We focus on opposite sex couples[10] aged between 25 and 64 earning positive income and find that assortative matching for this group in all urban areas has increased. Contrary to popular opinion and overseas evidence, educational assortative matching fell at the extremes of the educational distribution (high-educated and low-educated) but increased in the middle of the educational distribution (other-educated). Spatially, assortative matching increased in metropolitan areas but fell in non-metropolitan areas. In all periods, educational assortative matching has an inequality-increasing impact on the distribution of income (around 20 percent of observed inequality in each period for those working full-time). Spatially, we find that the effect of assortative matching on income inequality is larger and increased faster in metropolitan areas as well.

While our study focuses on the correlation between changes in educational assortative matching and changes in the distribution of income, the results cannot be given a clear causal interpretation[11]. Indeed, our method can be interpreted as representing an accounting approach that can only be regarded as a first-order approximation of the effect of assortative matching on the distribution of income. However, other recent work, such as Eika, Mogstad and Zafar (2014), Greenwood, Guner, Kocharkov and Santos (2014) and Kuhn and Ravazzini (2017) takes the same approach.

The rest of the study proceeds as follows: the next section discusses the existing literature on the relationship between assortative matching and the distribution of income; Section 3 introduces the data and methodology; Section 4 provides descriptive evidence and results from our counterfactual randomisation methodology; and section 5 concludes.

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[10] At the 2006 census, less than one percent of people living in couple families had reported to be in a same-sex partnership (see Statistics New Zealand, 2010). Also, the statistical coding of couple families as either opposite-sex or same-sex couples began with the 1996 census. For Censuses pre-1996, if a household consisted of an adult male and an adult female it was difficult to separate whether they were in a relationship, or were a brother and sister living together or were just flatmates.

[11] While assortative matching is likely to impact on the distribution of household income, changes in the distribution of income for other reasons may trigger changes in educational assortative matching as well. For example, personal income influences the social networks a person belongs to, which in turn impacts on partner selection.

2 Literature Review

The literature on assortative matching is extensive[12]. Interest in the role of educational assortative matching has a long history that can be traced back to Becker's (1973, 1981) seminal work on marriage and the family; and empirical works like Blackburn and Bloom (1987, 1994), and Cancian and Reed (1998, 1999) that explains changes in the distribution of family income. In this review, we present evidence from the earlier studies as well as discuss limitations of their approaches. We examine the different methodological approaches that are common in recent studies and what the differences in approach imply for the evidence of assortative matching on inequality. Finally, we review the available descriptive evidence on educational assortative matching in New Zealand.

Assortative matching could be on other characteristics such as age, ethnicity, religion, as well as earnings. Our study focuses on educational assortative matching and its impact on the distribution of income, thus our review is limited to a subset of studies focusing on education assortative matching. For a broader review of the literature on assortative matching, see Kalmijn (1998) and Schwartz (2013).

Early studies of educational assortative matching typically use the correlation between couples' level of education and the proportion of couples with the same level of education as evidence of assortative matching[13]. For example, Schwartz and Mare (2005) examined educational assortative marriage from 1940 to 2003 in the United States using Census and survey data. They find increasing resemblance of spouses in terms of educational attainment. They show that educational homogamy decreased from 1940 to 1960 but increased from 1960 to 2003. Their conclusion was already earlier reached by Kremer (1997) and Pencavel (1998) who focused on the same period in the US.

Blossfeld and Timm (2003) provide evidence from 12 European countries and the United States. In eight countries, they compared observed rates of marriage to random marital matching in each birth cohort. They find evidence of increased homogamy in marriage; specifically, they concluded that people seem to prefer to a large extent to marry an equally educated partner in these countries. Macfarlane (2016) also conducted a comparative analysis of assortative matching in European countries using data from 29 countries in the 2012 European Social Survey and found evidence of assortative matching in each country.

Alongside the descriptive studies, earlier studies that linked assortative matching to the distribution of income focused on the effect of changing correlation of husband-wife earnings on

[12] This topic has generated interest from sociologist, demographers and economists. Asides from its effect on income inequality, sociologist are typically also interested in assortative matching because of its implication for social rigidity, exclusion and social openness (see Blossfeld, 2009)

[13] Another important thing to note with earlier studies is that they were mostly focused on legally married couples, so most of the literature is framed in terms of husband and wives. More recent studies have focused on legal marriage as well as people who are in de-facto relationships and cover both same-sex and different-sex couples (e.g. Verbakel and Kalmijn on Dutch couples in 2014 Journal of Marriage and Family)

overall income inequality. For example, Burtless (1999) finds that around 13 percent of the rise in household inequality was due to an increase in the correlation of husband and wife earnings. Other studies have adopted a decomposition approach especially of the Coefficient of Variation measure[14]. Changes in the inequality of household earnings are decomposed to parts resulting from changes in the earning inequality of husbands, changes in the earning inequality of wives as well as the correlation between husband and wives' earnings. The changes due to the correlation between husband and wife earnings are taken as evidence of assortative matching. Other things being equal, an increase in the correlation of earnings between husband and wife will increase overall household inequality. Cancian, Danziger and Gottschalk (1993) and Blackburn and Bloom (1994) present evidence of such inter-spousal correlation coefficient increase.

Schwartz (2010) notes the limitation of the changes in correlation coefficient approach as a measure of changing association between spousal earnings. She proposes a modelling approach that "differentiates between earners and non-earners and incorporates measures of shrinking economic differences between spouses both in terms of their earnings relative to other members of their own sex" (p.1526). Depending on the measure of inequality used, her study found a stronger association of earnings between couples as responsible for around 25-30 percent of the increase in inequality. Furthermore, Gihleb and Lang (2016) make an important point on the use of the correlation coefficient of educational levels of partners as a measure of assortative matching. They argue that due to the ordinal nature of most educational classifications, rank correlation measures are typically employed, but these measures, such as the Spearman Rank correlation measure, do not perform well in measuring association in data with lot of ties such as ordinal educational levels. Further criticisms of assortative matching studies based on measures of association of income or education between spouses are that, firstly, other secular factors like changes in the educational distribution and, secondly, increased labour force participation of women could also be responsible for increased inter-spousal correlation in education and/or earnings (see Eika et al. 2014).

Recent studies have addressed the limitation of earlier studies by adopting a counterfactual randomisation approach to measuring assortative matching as well as to its effect on income inequality (Greenwood et al., 2014, Eika et al., 2014, Hrysho, Juhn and McCue, 2017). An increase in the number of couples with the same level of education does not imply an increase in assortative matching because factors like secular increase in educational attainment will increase the marginal distribution of educated people and thus increase the chances of couples being in the same educational group even though the rate of assortative matching has

[14] See Cancian, Danziger and Gottschalk (1993) and Blackburn and Bloom (1994) Cancian and Reed (1999) for further evidence. Breen and Andersen (2012) and Breen and Salazar (2011) use a counterfactual decomposition technique based on decomposing generalised entropy measures such as the Theil measure and Mean Log Deviation (MLD).

not changed. For example, in New Zealand, our data show that the proportion of people with higher education increased from 9 percent in 1986 to 32 percent in 2013. Hence even if the rate of assortative matching has not changed, there will be more couples with both having a high level of education, simply because that there are more educated people.

These studies compare the actual changes to what would have happened if there was random partnering. If the ratio of actual to random partnering is greater than one, it means the proportion of couples in the same educational category is greater than what may be expected if matching was random and there is then evidence of sorting of couples into that category. Eika et al. (2014) use a similar approach and create a sorting parameter S_{ij} based on the ratio of the observed probability that a husband with education level i is married to a wife with education level j relative to the probability under random matching with respect to education. By comparing the actual probability to the probability if matching was random, this method accounts for changes in the marginal distribution of education.

However, there are two major distinct approaches in the counterfactual randomisation methodology; the additional randomisation approach and the imputation randomisation approach (Harmenberg, 2014). The key differences between both approaches are well noted in Harmenberg (2014) and in Frémeaux and Lefranc (2017) and are summarised here. In the additional randomisation approach, individual incomes are held constant and treated like a fixed individual characteristic. The randomised counterfactual in this approach is based on a distribution where couples are randomly matched into couples but keep their actual observed income. This approach is limited because it does not allow for endogenous labour supply responses. This method assumes income and labour supply decisions are independent of household formation. Instead, there is in reality no reason to believe that, for example, a nurse partnered to a teacher will work the same hours and thus earn the same income than if that same nurse was partnered to a plastic surgeon.

The imputation randomisation accounts for these endogenous labour supply responses by taking household income as given instead of individual incomes. In this approach, individuals are randomly matched into couples and their household income is imputed based on household income of actual couples with the same observed characteristics. For example, assume that we create by randomisation a pseudo-household consisting of one lawyer and one doctor, the household income of this pseudo-household will be decided by randomly selecting from the household income of actual households with the same characteristics i.e. households in the actual distribution with a lawyer and a doctor. This approach is limited by how well labour supply decisions are driven by observed characteristics of couples. Harmenberg (2014) gives an important illustration in this regard – "there are strong reasons to believe that young men with no high school degree who are married to old women with more than a college degree are systematically different from young men with no high school degree married to young women

with no high school degree" (p.2). In addition, there is also the possibility that we might have randomised pseudo-households for which there are no actual households with the same actual characteristics.

Other studies like Pestel (2015) and Frémeaux and Lefranc (2017) have suggested some other approaches to account for endogenous labour supply decisions. Pestel (2017) accounts for endogenous labour supply by developing a structural model of household labour supply decisions using conditional logit while Frémeaux and Lefranc (2017) suggest using potential earnings instead of annual income. Potential earning is in this case defined as the earnings which an individual will receive if he/she worked full-time. The benefit of using potential earning is its independence from joint labour supply decisions since it is not dependent on hours worked unlike actual observed earnings.

The implication of the differences in randomisation techniques, when estimating the assortative matching impact on the distribution of income, may not be trivial. It depends on the extent of endogenous labour supply responses. Estimates from the additional randomisation approach will be smaller since endogenous labour supply responses typically dampen the effect of assortative matching (Harmenberg, 2014). Evidence from Pestel (2017) shows a assortative matching has a pronounced effect after adjusting for joint labour supply behaviour in West Germany.

Empirical evidence on the effect of educational assortative matching is mixed. Hryshko et al. (2017) and Eika et al. (2014) have found a small positive effect of assortative matching on income inequality in the US. This is contrary to the evidence from Breen and Salazar (2011) for the US where they found educational assortative matching to have a small negative effect on income inequality. In Brazil, where inequality fell, Hakak and Firpo (2017) found assortative matching reduced between 1990 and 2015 and this had very little effect on income inequality over this period. Evidence from Denmark in Breen and Andersen (2012) suggests that changes in the educational distribution rather than educational assortative matching drove the growing inequality in Denmark between 1987 and 2006.

Given the methodological issues, it is unsurprising that evidence on the role of assortative matching on income inequality seems inconclusive. Blossfeld (2009) highlights issues that lead to inconsistent findings. First, most studies are based on arbitrary classification of educational levels, and aggregation of educational levels might distort measures of educational homogamy[15]. Secondly, most studies are based on cross-sectional data. While some focus on first marriage, others often use the whole marriage stock. Analysis using the whole marriage stock may be reflecting the combined effect of other factors that drive re-marriage (Blossfeld, 2009, p.517).

[15] Gihleb and Lang (2016) also make a similar point.

We conclude this section by reviewing the available descriptive New Zealand evidence on educational assortative matching and changes in the educational distribution. To date, no study has linked educational assortative matching to income inequality in New Zealand. Callister and Didham (2010, 2014) use Census data on the 25-34 age group to document changes in educational distribution as well as education assortative matching. They found that between 1986 and 2013, the proportion of couples aged 25 to 34 years where both have a degree or higher has significantly increased from 4.2% to 23.1% while the proportion of couples in this age group where neither holds a formal qualification has declined from 14% to 3.3%. In the 20-year period between 1986 and 2006, there was a complete reversal in the ratio of education attainment between men and women. In 1986, 45 percent more males than females were holders of a Bachelor degree or higher. By 2006, there had been a complete reversal with 45 percent more women holding a Bachelor degree than men and by 2013, there were 53 percent more women with Bachelor's degree than men. On assortative matching, they conclude that it is the well-educated who are most likely to be partnered, and if partnered, they tend to have similarly qualified partners. At the same time, those with no formal education are less likely to be partnered, but if partnered they were in 2013 more likely to be with an unqualified partner. They conclude that these patterns and changes will have significant implications for income inequality in New Zealand. In this paper we extend Callister and Didham's (2010, 2014) analysis to the population aged 25-64 and link educational assortative matching to the distribution of income.

The next section details the data and methodology used.

3 Data and Methodology

3.1 Data

The data used are from the unit records of the usually resident New Zealand population from each of the six Censuses of Population and Dwelling between 1986 and 2013[16]. New Zealand Census data capture information on a host of socio-demographic characteristics including qualification, income, partnership status and location. Our target population are couples residing in the 40 Main and Secondary urban areas[17]. We define couples as male-female partners who are usually resident in the same household. We focus on male-female couples because the census (especially the earlier ones) did not ask questions on the gender of partners which makes it

[16] See also footnote 5.

[17] The 40 urban areas were grouped into metropolitan and non-metropolitan areas. Metropolitan areas are the urban areas in the six largest cities of Auckland, Christchurch, Wellington, Hamilton, Tauranga and Dunedin. We use the 2013 Statistics New Zealand definition of urban areas for all periods. The metropolitan areas account for about three quarters of all urban population. The rural population, which is excluded from the data, accounts for only about 14 percent of New Zealand's population.

impossible to separate those in a same-sex relationship from people of the same sex merely living in the same dwelling. Specifically, we identify couples by the answer to the "role in the family" question (if either parent and or spouse). We limit our analysis to those in the 25 to 64 age group working full-time and earning positive income to make our analysis reflective of labour market earnings. The age restriction is because the effect of education on income is likely to work through the labour market, we expect this mechanism to be at play the most in the 25-64 age range as most of the under 25 are either in education or training while the 65s and over will largely be out of the labour force. We limit the study to those working full-time in an attempt to limit joint labour supply responses through hours worked that may affect our estimates of the effect of assortative matching. Thus, the reported effect may be seen as an upper bound to the effect that would result when endogenous labour supply responses are taken into account.

Education is measured in terms of qualification achievement and we have three categories: High-educated (those with a Bachelor degree and above), Other-educated (those with other forms of qualification but below the Bachelor level) and Low-educated (those with no qualification). The inconsistencies in qualification classification over different censuses prevents using a more detailed educational grouping

Our income measure is the sum of personal income of individuals in couples. New Zealand Census income is typically captured in bands with the top income band open-ended[18]. We assume each individual earns the average of the income band he or she belongs to[19], and we assume a Pareto distribution for the top open-ended band. The average in the top band have been are calculated using the Stata RPME command developed by von Hippel et al. (2016). Our measure of inequality is the Mean Log Deviation. This measure is one of the generalised entropy measures. Full description of this measure and its properties can be found in Shorrocks (1980) or Bourguignon (1979) and this measure has been used to examine changes in the distribution of income in New Zealand in Alimi et al. (2018a) and in Alimi et al. (2018b).

One important feature of the present study is that we examine the effect of assortative matching on income distribution at the sub-national level. Previous studies have been at the national level but the inter-relationship between self-selection of educated people into cities, assortative matching and household income may have implications for spatial differences in the distribution of income. In addition to examining all urban areas combined, we focus on metropolitan areas (defined as the urban areas that make up the six largest cities in New Zealand) as well as non-metropolitan areas (all other urban areas).

[18] The issue with top open-ended bands are well known. For example, see Breen and Salazar (2011) for US data and Karagedikli et al. (2000) for New Zealand census data.

[19] The availability of income in bands may have implications for our measure of inequality. The MLD assumes every individual earns the midpoint of the income band it belongs. Not accounting for within-band variation may lead to under-estimation of actual inequality.

3.2 Methodology

We follow the additional randomisation counterfactual methodology. The advantages of this methodology are well detailed in Harmenberg (2014). We favour this methodology due to its directness and no requirement for imputation of income based on observed characteristics. In the additional randomisation approach, household income is assumed to be fixed and the effect of assortative matching on the distribution of income is estimated by comparing the observed distribution of income with a counterfactual distribution where matching is random. Although the method has been criticised for not accounting for endogenous labour supply responses, we limit some of the impact of this issue in our study by focusing only on couples where both partners are working full-time.[20]. Everyone working full time is classified into one of the three educational categories described earlier and education is measured as a household attribute.

For each Census period, let $f_Y^M(y;x)$ represent the distribution of income in an area M where M could be all urban areas combined, or a metropolitan area or a non-metropolitan area, then $f_Y^M(y;x) = \int f_{y|x}^M \ dF_X^M$ where $f_{y|x}^M$ respresents the education-specific conditional distribution and dF_X^M represents the prevalence of different household-level education mixes between couples. To illustrate, given our three levels of education – Highly Educated (H), Other Educated (O) and Low Education (L), there are six types of education mixes for couples[21,22]:

- HH- two high-educated partners
- HO /OH - one high-educated partner and one other-educated partner
- HL /LH - one high-educated partner and one low-educated partner
- OL /LO - one other-educated partner and one low-educated partner
- OO - two other-educated partners
- LL- two low-educated partners

Assortative matching on education and changes in the educational distribution will affect the prevalence rate of household-education types i.e. dF_X^M.

By comparing the actual distribution to a counterfactual distribution based on randomisation of partnering, we can net out the effect of changes in the educational distribution. The counterfactual distribution is the distribution of income in area M based on randomising the different types of educational pairing i.e. $\breve{f}_Y^{M|R} = \int f_{y|x}^M \, dF_{RX}^M$. Where dF_{RX}^M represent prevalence

[20] Although one may argue that there could be endogenous responses in terms of type of job taken even if hours do not change

[21] There will be 9 types of couples if we account for ordering i.e. male=L and female=H is seen as different from male= H and female=L. The distinction could matter when there a large gender pay gap, given education. In New Zealand, was gap has reduced to 9.4 percent by 2017 (Ministry of Women; women.govt.nz, accessed 2/8/2018. Ignoring the gender assignment in the education paring is unlikely to have affected the conclusions of this paper.

[22] Note that if there is a large gender gap in earnings, HO and OH have different expected levels of income. Ditto for HL/LH and OL/LO

of household-education types based on random matching. The effect of educational assortative matching is the difference between these two distributions:

$$f_Y^M - \check{f}_Y^{M|R}$$

We use the MLD as a summary measure of the observed f_Y^M and counterfactual distribution $\check{f}_Y^{M|R}$ and the differences in this measure for the two distributions are compared. As well as the unconditional randomisation, we perform several other conditional randomisations where we hold observed characteristics like age, qualification and location constant. These conditional randomisations give us an estimate of the role of sorting on these observed characteristics. Our conditional randomisations are:

- Age conditional: randomising but holding the actual age distribution constant i.e. partnering is random but people are randomly partnered to someone else with the same age as their observed partner
- Qualification conditional: randomising but holding the actual qualification distribution constant i.e. partnering is random but people are randomly partnered to someone else with the same education as their actual observed partner
- Age and qualification conditional: randomising but holding both the actual age and education distribution constant i.e. partnering is random but people are randomly partnered to someone else with the same age and education as their actual observed partner
- Age, qualification and location conditional: randomising but holding the actual age, qualification and spatial distribution (urban area) constant i.e. partnering is random, but people are randomly partnered to someone else with the same age, education, and location as their actual observed partner.

As in Kuhn and Ravazzini (2017), we also provide some approximate estimate of the potential of assortative matching on the distribution of income by assuming extreme levels of assortative matching. We sort the population first on education and then on income bands, i.e. we rank the population from the highest educated to the lowest educated and now sort on income within each education categories. We consider two additional counterfactual distributions: in the first counterfactual, we partner the highest ranked male to the highest ranked female, the second highest ranked male to the second highest ranked female and so on. This gives an estimate of what the distribution of income will be like under maximum assortative matching. In the second counterfactual, we partner the highest ranked male by education and income to the least ranked female, the second highest ranked male to the second to the least ranked female and so on. This represents a scenario of maximum disassortative matching and we examine what the distribution of income will be like under this assumption.

In the next section we provide descriptive evidence on educational assortative matching as well as results from our counterfactual randomisation methodology.

4 Results: Educational Assortative Matching and Income Inequality in New Zealand

We begin this section by describing the distribution of individual income of those participating in the labour force (full-time employed, part-time employed and unemployed). While we will focus on assortative matching of those in full-time employment only, we first consider everybody in the labour force, including those employed part-time and those unemployed, to show the important contribution of those working full-time to inequality. Next, we shift the level of analysis to couples and focus on the income distribution of male-female couples working full-time and earning positive income and finally we examine descriptive evidence on the patterns and changes in educational assortative matching. Aside education, we also provide some evidence on occupational assortative matching using the 1-digit New Zealand Standard Classification of Occupation (NZSCO99). In the final section, we link assortative matching to the distribution of income.

4.1 Patterns and changes in the personal income distribution for individuals participating in the labour force

The trends and patterns in income distribution of the 25 to 64 age group earning positive income has already been described in Alimi et al. (2018b). Inequality in individual incomes increased by around 1 percent in all urban areas. This figures hides the spatial disparity, inequality fell in non-metropolitan areas (-11 percent) and rose in metropolitan areas (4 percent) between 1986 to 2013[23].

For those participating in the labour force (i.e full-time employed, part-time employed and unemployed), we find higher rates of growth in inequality of individual incomes. From 1986 to 2013, personal income inequality increased by around 23 percent in all urban areas, mostly driven by increases in metropolitan areas (27 percent) and to a lesser extent by increases in non-metropolitan areas (8 percent).

We decompose the inequality in each census period by labour force status. Inequality among the full-time employed is a important component of inequality of those earning labour income. We find that within-labour force status group inequality account for most of overall inequality (around 78-84 percent of overall inequality, see Table 1) and those working full-time contribute around two-thirds of within-labour force status group inequality.With respect to between-labour force status group inequality, it accounts for around 17 to 22 per cent of overall inequality. Not suprisingly, given the large differences in income between full-time workers, part-time workers and the unemployed, this percentage share is higher than in the case of between-age inequality reported in Alimi et al. (2018a) or between-migrant group inequality in

[23] See Appendix 1 for summary from Alimi et al. (2018).

Alimi et al. (2018b). In Table 1, we present the decomposition of overall inequality into between and within components and the contribution of each labour force groups for all urban areas[24].

Table 1: Decomposition of personal income inequality (MLD) by labour-force groups: All urban areas combined

Labour force groups	1986	1991	1996	2001	2006	2013
			National			
Between-group contribution						
Full-time	-0.0945	-0.1081	-0.1120	-0.1109	-0.0951	-0.1028
Part-time	0.1108	0.1036	0.1219	0.1259	0.1148	0.1151
Unemployed	0.0351	0.0609	0.0517	0.0468	0.0264	0.0423
Sum between-group	0.0514	0.0564	0.0616	0.0618	0.0461	0.0546
Between as a prop. of total	21.5%	22.0%	20.6%	20.3%	16.5%	18.6%
Within-group contribution						
Full-time	0.1226	0.1302	0.1588	0.1667	0.1610	0.1651
Part-time	0.0493	0.0506	0.0641	0.0613	0.0619	0.0564
Unemployed	0.0158	0.0189	0.0151	0.0146	0.0106	0.0171
Sum within-group	0.1877	0.1997	0.2380	0.2426	0.2335	0.2386
Full-time as a prop. of sum within-group	65.3%	65.2%	66.7%	68.7%	69.0%	69.2%
Total (sum between-group + sum within-group)	0.2392	0.2561	0.2997	0.3044	0.2795	0.2932
Sum within as prop of total-inequality	78.5%	78.0%	79.4%	79.7%	83.5%	81.4%

Notes: Results are the between and within-group contribution to overall inequality (as measured by the MLD) for those participating in the labour force in all urban areas combined (full-time employed, part-time employed and unemployed)

4.2 Patterns and changes in the distribution of income of male-female couples working full-time

We shift our level of analysis to couples and examine the patterns and changes in the distribution of total income of male-female couples working full-time. In Table 2, we present the trend in average incomes and the MLD for the different types of couples (classified by their education levels) from 1986 to 2013 for all urban areas[25]. For all couples working full-time (regardless of educational level) , real average income increased by 28 percent between 1986 and 2013. Unsuprisingly, couples where both partners are highly educated had the highest mean incomes while couples with two low education partners had the lowest average incomes in all periods. Indicative of the gap between high-educated and low-educated couples, the average income in couples with two high-educated partners were more than double that of low-educated

[24] Decomposition results for Non-metropolitan and Metropolitan areas are available in Appendix 2 and Appendix 3 respectively.
[25] Tables for Non-metropolitan and Metropolitan Areas are available in Appendix 4 and Appendix 5 respectively.

partners in all periods except in 1986. The gap between high-educated and low-educated couples widened over time; between 1986 and 2013, high-educated couples had the highest growth in average incomes at 19 percent compared to 6 percent for low-educated couples.

As measured by the MLD, overall inequality for all couples working full time grew by around 49 percent. This masks the variation across couple types. Inequality grew the most in couples with two high-educated partners at 55 percent compared to 1 percent growth for couples with a mix of one high-educated and a low-educated partner (HL/LH)[26]. In all periods, within-group inequality is lowest among couples with a mix of an other-educated and a low-educated partner (OL/LO). Prior to 1996, couples with a mix of a high-educated and a low-educated partner had the highest within-group inequality but from 1996, high-educated couples had the highest within-group inequality.

[26] Note that there may be a slight difference between HL and LH that is not being considered here.

Table 2: Mean and inequality statistics by couple type in each census period for all urban areas combined

All urban areas combined						
1986	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall-mean			$95,696			
Group-mean	$144,627	$126,924	$99,873	$114,930	$87,853	$77,594
Rel. mean income	1.51	1.33	1.04	1.20	0.92	0.81
By-group MLD	0.0895	0.0849	0.0766	0.0969	0.0712	0.0747
Pop share	4.0%	8.3%	35.1%	1.0%	30.3%	21.3%
Overall MLD			0.0895			
1991	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$101,260			
Group-mean	$158,934	$136,119	$101,400	$117,485	$87,594	$75,510
Rel. mean income	1.57	1.34	1.00	1.16	0.87	0.75
By-group MLD	0.0981	0.0953	0.0898	0.1133	0.0845	0.0859
Pop share	5.7%	10.3%	43.3%	0.9%	26.3%	13.5%
Overall MLD			0.1089			
1996	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$111,133			
Group-mean	$164,184	$141,788	$109,434	$124,748	$94,672	$80,782
Rel. mean income	1.48	1.28	0.98	1.12	0.85	0.73
By-group MLD	0.1235	0.1078	0.0921	0.1171	0.0909	0.0916
Pop share	8.6%	13.2%	39.1%	1.4%	24.2%	13.6%
Overall MLD			0.1179			
2001	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$120,852			
Group-mean	$175,377	$149,102	$113,880	$127,878	$97,652	$83,046
Rel. mean income	1.45	1.23	0.94	1.06	0.81	0.69
By-group MLD	0.1257	0.1170	0.1050	0.1142	0.0931	0.0946
Pop share	10.1%	17.0%	45.3%	1.3%	18.5%	7.8%
Overall MLD			0.1278			
2006	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$125,310			
Group-mean	$167,719	$144,913	$116,647	$125,936	$100,984	$83,589
Rel. mean income	1.34	1.16	0.93	1.00	0.81	0.67
By-group MLD	0.1347	0.1159	0.1086	0.1039	0.0938	0.0977
Pop share	14.2%	20.6%	41.5%	1.6%	16.0%	6.1%
Overall MLD			0.1285			
2013	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean (2013$)			$131,754			
Group-mean	$172,684	$145,312	$117,609	$123,541	$101,156	$82,252
Rel. mean income	1.31	1.10	0.89	0.94	0.77	0.62
By-group MLD	0.1391	0.1180	0.1097	0.0978	0.0900	0.1045
Pop share	18.8%	25.1%	39.0%	1.8%	11.4%	3.9%
Overall MLD			0.1333			
All reported mean and group-mean are in 2013$						

Notes: Results are the mean, relative mean income, MLD and population share for each educational pair and the overall mean income in all urban areas combined in each census period. Abbreviations: HH- two high-educated partners; HO /OH - one high-educated partner and one other-educated partner; OO - two other-educated partners; HL/LH - one high-educated partner and one low-educated partner; OL /LO - one other-educated partner and one one low-educated partner; LL - two low-educated partners

Table 3: Inequality of total income of male-female couples working full-time and aged 25-64 from 1986 to 2013

Area	1986	1991	1996	2001	2006	2013	Growth 1986-2013
Non-metro	0.0837	0.0999	0.1039	0.1121	0.1109	0.1092	30%
Metro	0.0906	0.1093	0.1194	0.1290	0.1308	0.1372	51%
All urban areas	0.0895	0.1089	0.1179	0.1278	0.1285	0.1333	49%

Notes: Results are MLD by area for each census period from 1986 to 2013. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Table 3 summarises the Mean Log Deviation (MLD) by area from 1986 to 2013. Inequality among couples working full-time is lower than personal income inequality of everyone in the labour force (compare Table 1 and Table 3) but grew faster. In all urban areas combined, inequality in total income of couples grew faster than national total household income inequality reported in Ball and Creedy (2016) and Perry (2017). In all urban areas combined, inequality in total income of couples working full-time grew by around 49 percent between 1986 and 2013 whereas national total household income inequality growth over the same period in Ball and Creedy (2016) is around 14 percent. Spatially, income inequality for full-time couples earning positive income grew in both metropolitan and non-metropolitan areas, with growth between 1986 to 2013 in metropolitan areas (51 percent) higher than in non-metropolitan areas (30 percent).

Our focus in this study is to examine the role of assortative matching in these patterns of inequality. Before we get to the evidence on the contribution of educational assortative matching to inequality in the next section, we provide here descriptive evidence on changes in the educational distribution and rates of assortative matching in all census periods and across the three spatial areas considered.

4.3 Patterns of educational assortative matching among male-female couples in New Zealand

As noted earlier, inter-temporal studies of assortative matching need to account for secular changes in the educational distribution in all urban areas. In Table 4, we show the changes in the educational attainment for males and females in couples[27]. We begin with all urban areas combined and proceed by examining the differences between metropolitan and non-metropolitan areas.

The secular increase in educational attainment is evident. In 1986, only 9 percent of the individuals who are married or in a de facto relationship could be classified as high-educated. By 2013, this proportion had increased to 32 percent. Educational attainment has risen faster for

[27] Tables for Non-metropolitan and Metropolitan Areas are available in Appendix 6 and Appendix 7

females. In 1986, there were 51 percent more males than females that are high-educated, by 2013 this proportion has reversed with 36 percent more females than males[28]. These changes in the educational distribution are significant and implies that even if underlying rates of assortative matching has not changed, there will be more couples with both having high education simply because there is a huge increase in the number of educated individuals (both males and females).

Table 4: Educational distribution for individuals in couples aged 25-64 in all urban areas from 1986 to 2013

	Total (Male + Female)	**Prop**	**Male**	**Prop.**	**Female**	**Prop**	**Ratio of Male/Female**
			1986				
High-Education	20,913	9%	12,588	10%	8,325	7%	151%
Other-Education	130,974	54%	67,485	56%	63,489	53%	106%
Low-Education	88,902	37%	40,323	33%	48,579	40%	83%
Total specified	240,789	100%	120,393	100%	120,393	100%	
			1991				
High-Education	28,758	11%	16,329	13%	12,426	10%	131%
Other-Education	157,134	62%	78,474	62%	78,663	62%	100%
Low-Education	69,126	27%	32,706	26%	36,420	29%	90%
Total specified	255,021	100%	127,509	100%	127,512	100%	
			1996				
High-Education	39,495	16%	21,285	17%	18,210	15%	117%
Other-Education	143,787	58%	69,582	56%	74,208	60%	94%
Low-Education	65,754	26%	33,651	27%	32,103	26%	105%
Total specified	249,039	100%	124,521	100%	124,518	100%	
			2001				
High-Education	58,554	19%	28,899	19%	29,658	19%	97%
Other-Education	191,853	63%	93,885	62%	97,971	64%	96%
Low-Education	53,838	18%	29,340	19%	24,495	16%	120%
Total specified	304,245	100%	152,121	100%	152,124	100%	
			2006				
High-Education	100,119	25%	45,429	23%	54,693	28%	83%
Other-Education	236,940	60%	120,261	61%	116,679	59%	103%
Low-Education	59,265	15%	32,475	16%	26,793	14%	121%
Total specified	396,327	100%	198,165	100%	198,162	100%	
			2013				
High-Education	132,855	32%	56,268	27%	76,584	37%	73%
Other-Education	235,983	57%	124,716	61%	111,267	54%	112%
Low-Education	43,350	11%	25,107	12%	18,240	9%	138%
Total specified	412,185	100%	206,094	100%	206,094	100%	

Notes: Results are the number and proportion by gender in each educational group in all urban areas combined for each census period. High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

[28] Note that the figures reported are different from the ones reported in Callister and Didham (2010,2014). Both studies by Callister and Didham focused on the whole population aged 25-34 while we focus on the population aged 25-64 in male-female couples, earning positive income and working full-time.

In Table 5, we present contingency tables showing in proportions, the actual pairing of couples with respect to their highest educational attainment and in Table 6, we present what the pairing would have been under an assumption of random matching. The random matching contingency tables are the average of 250 replications of randomisation with the standard errors in brackets.[29]

Table 5: Actual proportion of couples in each educational pairing from 1986 to 2013: All urban areas combined

Female	**Male**		
	High-education	Other-education	Low-education
		1986	
High-Education	4.0%	2.5%	0.4%
Other-Education	5.8%	35.1%	11.8%
Low-Education	0.7%	18.4%	21.3%
		1991	
High-Education	5.7%	3.6%	0.4%
Other-Education	6.7%	43.3%	11.7%
Low-Education	0.5%	14.6%	13.5%
		1996	
High-Education	8.6%	5.4%	0.7%
Other-Education	7.8%	39.1%	12.7%
Low-Education	0.7%	11.5%	13.6%
		2001	
High-Education	10.1%	8.6%	0.8%
Other-Education	8.4%	45.3%	10.7%
Low-Education	0.4%	7.8%	7.8%
		2006	
High-Education	14.2%	12.2%	1.2%
Other-Education	8.3%	41.5%	9.0%
Low-Education	0.4%	7.0%	6.1%
		2013	
High-Education	18.8%	16.9%	1.5%
Other-Education	8.2%	39.0%	6.8%
Low-Education	0.3%	4.6%	3.9%

Notes: Results are the actual proportion of male-female couples in each educational pairing in all urban areas combined for each census period. High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification.

[29] Non-metropolitan area tables are available in Appendix 8 and Appendix 9 and Metropolitan area tables in Appendix 10 and Appendix 11.

Table 6: Proportion of couples in each educational pairing from 1986 to 2013 under randomisation: All urban areas combined

Random pairing- All urban areas			
Female	**Male**		
	High-education	Other-education	Low-education
1986			
High-Education	0.7% (0.02%)	3.9% (0.04%)	2.3% (0.04%)
Other-Education	5.5% (0.05%)	29.6% (0.07%)	17.7% (0.07%)
Low-Education	4.2% (0.05%)	22.6% (0.07%)	13.5% (0.07%)
1991			
High-Education	1.3% (0.03%)	6.0% (0.04%)	2.5% (0.04%)
Other-Education	7.9% (0.05%)	38.0% (0.06%)	15.85% (0.06%)
Low-Education	3.7% (0.04%)	17.6% (0.06%)	7.35% (0.05%)
1996			
High-Education	2.5% (0.04%)	8.2% (0.05%)	4.0% (0.04%)
Other-Education	10.2% (0.05%)	33.3% (0.08%)	16.1% (0.07%)
Low-Education	4.4% (0.05%)	14.4% (0.07%)	7.0% (0.06%)
2001			
High-Education	3.7% (0.04%)	12.0% (0.05%)	3.8% (0.04%)
Other-Education	12.2% (0.05%)	39.7% (0.06%)	12.4% (0.05%)
Low-Education	3.1% (0.04%)	9.9% (0.04%)	3.1% (0.04%)
2006			
High-Education	6.3% (0.04%)	16.7% (0.05%)	4.5% (0.04%)
Other-Education	13.5% (0.05%)	35.7% (0.06%)	9.7% (0.04%)
Low-Education	3.1% (0.03%)	8.2% (0.04%)	2.2% (0.03%)
2013			
High-Education	10.1% (0.05%)	22.5% (0.06%)	4.5% (0.03%)
Other-Education	14.7% (0.05%)	32.7% (0.06%)	6.6% (0.03%)
Low-Education	2.4% (0.03%)	5.4% (0.03%)	1.1% (0.02%)

Notes: Results are the proportion of male-female couples in all urban areas combined in each educational pairing in each census period under randomised matching. High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

The actual pairings show a relatively large proportion of couples with the same level of educational attainment, i.e. couples along the diagonal. Education-matched couples represent about 60-63% of all couples. Interestingly, there is no clear upward trend in this percentage. Examining changes in the proportions along the diagonal over time will lead to an incorrect conclusion that assortative matching has increased for the high-educated and decreased for the lowly educated. Although the proportion of couples where both partners are high-educated increased from 4 percent in 1983 to 19 percent in 2013, while the proportion of couples with both a low education reduced from 21.3 percent in 1983 to 3.9 percent in 2013, these changes reflect the combined effect of changes in assortative matching and changes in the educational distribution. Indeed, looking at the numbers from the random distribution (Table 6), we find that if matching was entirely random, the proportion of couples where both partners are high-educated will have increased from around 1 percent in 1986 to 10 percent in 2013 while couples

with no qualification will have fallen from 14 percent in 1986 to 1 percent in 2013. Even without assortative matching, changes in the educational distribution would have led to a large increase in the proportion of couples with a high level of education attainment and a reduction of those with low level of education attainment.

To disentangle the changes in educational distribution from the role of assortative matching, the standard approach in the literature is to calculate the concentration ratio i.e. the ratio of the actual to random in each educational pair[30]. A ratio greater than one is indicative of a greater concentration than would be expected under random matching and evidence of assortative matching. This ratio for all urban areas, reported in Table 7[31] reveals the extent to which each educational pairings occur above what will have happened if matching was random given the educational distribution. However, we argue that the concentration ratio is rather strongly influenced by the population proportions in relatively rare education pairings and may lead to misleading conclusions on the trend in educational assortative matching.

[30] See Callister and Didham (2010,2014) and Greenwood et al. (2014)
[31] See Appendix 12 for Non-metropolitan ratios and Appendix 13 for Metropolitan ratios

Table 7: Concentration ratio: All urban areas combined

Female	**Male**		
	High-Education	Other-Education	Low-Education
	1986		
High-Education	5.6	0.7	0.2
Other-Education	1.1	1.2	0.7
Low-Education	0.2	0.8	1.6
	1991		
High-Education	4.5	0.6	0.2
Other-Education	0.8	1.1	0.7
Low-Education	0.1	0.8	1.8
	1996		
High-Education	3.4	0.7	0.2
Other-Education	0.8	1.2	0.8
Low-Education	0.2	0.8	2.0
	2001		
High-Education	2.7	0.7	0.2
Other-Education	0.7	1.1	0.9
Low-Education	0.1	0.8	2.5
	2006		
High-Education	2.2	0.7	0.3
Other-Education	0.6	1.2	0.9
Low-Education	0.1	0.9	2.8
	2013		
High-Education	1.9	0.8	0.3
Other-Education	0.6	1.2	1.0
Low-Education	0.1	0.9	3.6

Notes: Results are the concentration ratio i.e. ratio of actual proportion to random proportion of male-female couples in each educational group in each census period for all urban areas combined. High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

We can conclude from Table 7 that between 1986 and 2013, assortative matching fell sizeably –relative to random sorting – for the high-educated pairs (from 5.6 to 1.9), remained constant for the other-educated pairs (from 1.2 to 1.2) and increased considerably for the low-educated pairs (from 1.6 to 3.6). This conclusion may however be misleading. The concentration ratio for groups with large population proportions will have a smaller range than for groups with small proportions and thus it is easier to conclude that smaller groups have bigger changes.

To see this clearly, let us assume, for ease of explanation, a contingency table with just 2 groups: high-educated and low-educated. The minimum the concentration ratio can be is 0, i.e. if the frequency of a pairing is zero. It will be 1 when, the actual proportion is equal to random proportion. However, the maximum value of the concentration ratio depends on the maximum possible homogamy that can be achieved given the educational distribution.

$$Max\ concentration\ ratio = \frac{\text{Max Homogamy}}{\text{Random}}$$

The maximum homogamy for each pair is the minimum of the male and female population proportion in that pair i.e. if there are 20 percent males with high education and 15 percent females with high education, the maximum possible proportion of people in the high-education pair (maximum homogamy) is 15 percent. In general, max homogamy= Min[$P(F_H)$), $P(M_H)$)]. Under random matching, the proportion of people in the high-educated group is $P(F_H) * P(M_H)$.

Since maximum homogamy is the minimum of the male and female proportions in that pair, the maximum possible value for the concentration ratio will be the inverse of the group with the larger proportions. [32]

This implies that:

- The ratio will be larger when both groups are small.
- If one or both groups are large, the ratio will be small

Since ratios are influenced by the population proportion, this may affect the conclusion we draw on the rates and trend in assortative matching. This has implications for our New Zealand data - the other-educated group has a large population proportion (see Table 5) and will always have smaller ratios compared to the other groups that have smaller proportions. Focusing on changes in the concentration ratios over time, may lead to incorrect conclusions on the trends of educational assortative matching.

Due to the effect population proportions can have on the concentration ratio, we propose a new measure of assortative matching. Our proposed index is calculated as :

$$Index = \frac{Actual - Random}{Max\ homogamy - Random}$$

[32] For example, if $P(F_H) < P(M_H)$ then the Max Homogamy fraction equals $P(F_H)$ and the random fraction equals $P(F_H) * P(M_H)$. Therefore the Max concentration ratio = $P(F_H)/(P(F_H)* P(M_H))$ = $1/P(M_H)$. Similarly, when $P(F_H) > P(M_H)$,the Max concentration ratio is $1/P(F_H)$)).

As described previously, $Max\ Homogamy$ is the maximum possible pairing for each educational pair. For example, in 1986, in all urban areas about 7 percent of the population were high-educated females and 10 percent were high-educated males, the maximum possible pairing for high-educated in this year is 7 percent i.e. if all high-educated people were partnered to each other, we would only have 7 percent of the population in the high-educated pair. Our index normalises the calculation of concentration in each educational pair and is not influenced by the population proportions. It will range between 0 and 1 for the same educational pairings (along the diagonals) [33]. Our index is equal to 0 if matching is entirely random and equal to 1 under if actual patterns of matching are equal to what will happen under maximum homogamy.

Like the concentration ratio reported in Table 7, we calculate our index for all educational pairs in all urban areas in Table 8 with standard errors in brackets.[34,35]. Our interest is in the diagonals (pairs with the same education).

[33] It is possible to get negative values for our index on the off-diagonal cells. Negative values on the off-diagonal cells are consistent with assortative matching while positive values in the off-diagonals are consistent with non-assortative matching, or even disassortative matching, which may also occur concurrently with assortative matching.

[34] See Appendix 14 for Non-metropolitan areas and Appendix 15 for Metropolitan areas

[35] Standard errors are the standard deviations from 250 replications of randomisation.

Table 8: Assortative matching index by educational group: All urban areas combined

Female	**Male**		
	High-education	Other-education	Low-education
		1986	
High-Education	0.53	-0.44	-0.42
	(0.2%)	(1.8%)	(1.1%)
Other-Education	0.06	0.24	-0.37
	(0.9%)	(0.2%)	(0.6%)
Low-Education	-0.57	-0.24	0.39
	(1.2%)	(0.5%)	(0.2%)
		1991	
High-Education	0.52	-0.63	-0.29
	(0.2%)	(1.8%)	(0.7%)
Other-Education	-0.25	0.23	-0.42
	(1.2%)	(0.2%)	(0.8%)
Low-Education	-0.35	-0.27	0.34
	(0.6%)	(0.7%)	(0.2%)
		1996	
High-Education	0.50	-0.44	-0.30
	(0.2%)	(1.1%)	(0.5%)
Other-Education	-0.35	0.26	-0.31
	(1.1%)	(0.2%)	(0.8%)
Low-Education	-0.29	-0.26	0.35
	(0.5%)	(0.7%)	(0.2%)
		2001	
High-Education	0.42	-0.47	-0.19
	(0.2%)	(1.0%)	(0.3%)
Other-Education	-0.56	0.25	-0.26
	(1.1%)	(0.2%)	(0.9%)
Low-Education	-0.20	-0.34	0.36
	(0.3%)	(1.0%)	(0.2%)
		2006	
High-Education	0.47	-0.42	-0.28
	(0.1%)	(0.6%)	(0.4%)
Other-Education	-0.55	0.25	-0.09
	(0.8%)	(0.2%)	(0.6%)
Low-Education	-0.26	-0.23	0.35
	(0.4%)	(1.0%)	(0.2%)
		2013	
High-Education	0.50	-0.38	-0.40
	(0.1%)	(0.6%)	(0.6%)
Other-Education	-0.52	0.30	0.04
	(0.6%)	(0.2%)	(0.6%)
Low-Education	-0.33	-0.21	0.37
	(0.6%)	(1.1%)	(0.2%)

Notes: Results are the educational assortative matching index calculated as $\frac{Actual-Random}{Max\ homogamy-Random}$ for each educational pairing for all urban areas combined in each census period. Standard errors in brackets (standard errors are the standard deviation of 250 replications of randomisation). High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

As in Table 7, we conclude on the basis of our relative homogamy index that assortative matching of those with high-education has declined and of those with other-education has increased, when comparing 1986 with 2013. However, contrary to the results from the concentration ratio, between 1986 and 2013,our index shows that assortative matching declined for the low-educated. In all cases, the index changes are relatively small as compared with the concentration ratio changes that suggested dramatic shifts in assortative matching. For the high-educated, our index declines from 0.53 in 1986 to 0.50 in 2013. For the low-educated, it declines from 0.39 in 1986 to 0.37 in 2013, while it increased from 0.24 to 0.30 for the other-educated. Our results are partially consistent with evidence from the US in Eika et al. (2014) which reports decreasing level of assortative matching among college graduates [36]. However, they report increasing assortative matching among those with no high school degree whereas in the NZ case assortative matching among the low-educated appears to be declining. Our findings are contrary to public commentary which suggest increases in assortative matching in recent years, especially for those at the top of the educational distribution[37].

Table 9 presents the index for the diagonal educational pairs for all areas (standard errors in brackets). Besides the diagonal educational pairs, we also compute a composite measure of assortative matching in each period. This is calculated as the weighted average of the diagonal index in each same education pair (along the diagonals) and the weights are the actual proportion of each educational pair in the actual distribution.

[36] Chiappori, Salanie and Weiss (2017) reports increased assortative matching for high-educated Whites in the US.

[37] For popular media, see the Cowen (2015) article in the *New York Times* and the Worstall (2015) article in the *Forbes* magazine.

Table 9: Assortative matching index by educational group for all areas

Educational assortative matching index						
Non-metro						
	1986	1991	1996	2001	2006	2013
High-Education	0.53	0.50	0.46	0.37	0.42	0.47
	(0.4%)	(0.3%)	(0.3%)	(0.3%)	(0.3%)	(0.3%)
Other-Education	0.23	0.22	0.24	0.22	0.18	0.21
	(0.4%)	(0.4%)	(0.5%)	(0.4%)	(0.4%)	(0.4%)
Low-Education	0.35	0.30	0.33	0.34	0.31	0.33
	(0.4%)	(0.3%)	(0.4%)	(0.4%)	(0.3%)	(0.4%)
All (Composite)	0.29	0.26	0.28	0.26	0.23	0.27
	(0.4%)	(0.4%)	(0.4%)	(0.4%)	(0.3%)	(0.3%)
Metro						
High-Education	0.53	0.52	0.51	0.42	0.47	0.50
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)
Other-Education	0.24	0.23	0.26	0.26	0.27	0.31
	(0.3%)	(0.2%)	(0.3%)	(0.2%)	(0.2%)	(0.2%)
Low-Education	0.40	0.35	0.36	0.37	0.35	0.38
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)
All (Composite)	0.32	0.28	0.32	0.30	0.33	0.38
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)
All urban areas						
High-Education	0.53	0.52	0.50	0.42	0.47	0.50
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.1%)	(0.1%)
Other-Education	0.24	0.23	0.26	0.25	0.25	0.30
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)
Low-Education	0.39	0.34	0.35	0.36	0.35	0.37
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)
All (Composite)	0.31	0.28	0.31	0.29	0.31	0.36
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)

Notes: Results are the educational assortative matching index for couples with same level of education in each period. Index is calculated as : $\frac{Actual-Random}{Max\ homogamy-Random}$. Standard errors in brackets (standard errors are the standard deviation of 250 replications of randomisation). High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

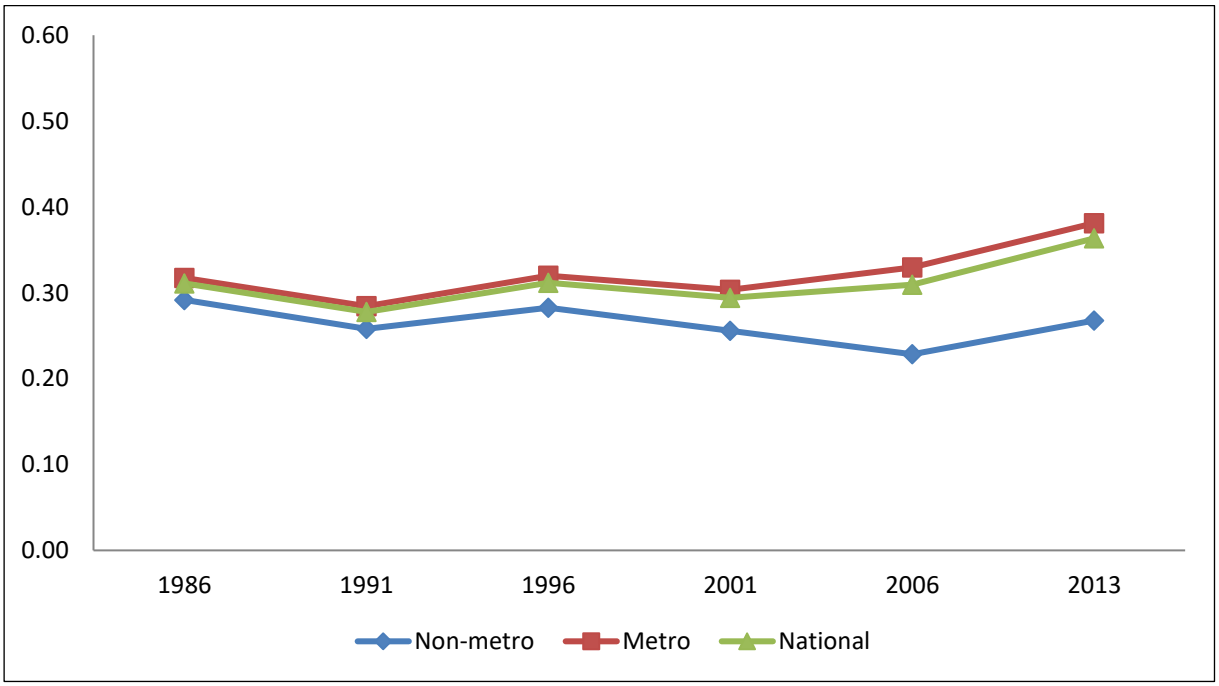
The composite index indicate overall increases in assortative matching in all urban area from 0.31 in 1986 to 0.36 in 2013. As shown by educational group, this increase is due to changes in the other-educated group (0.24 to 0.30) rather than changes for the high-educated or low-educated.

Spatially, between 1986 and 2013, assortative matching fell in non-metropolitan areas while it rose in metropolitan areas. In both areas, the changes in assortative matching are similar for the high-educated and the low-educated: assortative matching fell. Nonetheless, there are some differences between metropolitan and non-metropolitan areas: firstly, assortative matching increased for the other-educated group in metropolitan areas contrary to non-metropolitan areas where it fell. The increase in assortative matching for the other-educated

group in metropolitan areas meant assortative matching increased overall in metropolitan areas. It is the increase in assortative matching for the other-educated in metropolitan-areas that actually drove the overall rise in assortative matching in all urban areas combined. Secondly, apart from 1986, in each educational group, assortative matching was higher in metropolitan areas than non-metropolitan areas and the difference across areas seem to be growing over time especially for high-educated and other-educated. This is unsurprising given that young educated people are attracted to metropolitan areas and in New Zealand, the metropolitan areas are also locations of universities which may function as a meet-market.

Figure 1 summarises the trend in assortative matching in by area in all periods.

Figure 1: Assortative matching index for couples with same category of education by area in all periods



Notes: Figure 1 presents educational assortative matching index for couples with same level of education in each area in each census period. Index calculated as $\frac{Actual-Random}{Max\ homogamy-Random}$. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

To conclude on the descriptive patterns of educational assortative matching in New Zealand, in all urban areas, we find evidence of increasing rates of educational assortative matching over time driven by increases in the assortative matching for the other-educated. By educational group, assortative matching has declined for both the high-educated and low-educated groups. Spatially, we find higher and incresaing rates of assortative matching in metropolitan areas compared to non-metropolitan areas.

As well as educational assortative matching, we examine occupational assortative matching over the 1986 to 2013 period. This is useful in the present context because occupation

is a strong predictor of income. We use a consistent 1-digit classification of occupations of the 1999 New Zealand Standard Classification of Occupations in all census periods[38]. We use our new index to examine the overall trend in occupational assortative matching in each census period by area[39]. We report the composite occupational assortative matching index by area in Table 10.

Table 10: Assortative matching index of occupational pairings of couples from 1986 to 2013 by area

	Occupational assortative matching index					
	Non-metropolitan					
	1986	1991	1996	2001	2006	2013
All (Composite)	0.29	0.28	0.25	0.24	0.20	0.19
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)	(0.2%)
	Metropolitan					
All (Composite)	0.24	0.24	0.22	0.21	0.19	0.17
	(0.2%)	(0.1%)	(0.2%)	(0.1%)	(0.1%)	(0.1%)
	All urban areas					
All (Composite)	0.26	0.25	0.23	0.22	0.19	0.18
	(0.1%)	(0.1%)	(0.1%)	(0.1%)	(0.1%)	(0.1%)

Notes: Results are the occupational assortative matching index for couples with same occupational classification in each census period by area. Index is calculated as : $\frac{Actual-Random}{Max\ homogamy-Random}$. Standard errors are the standard deviations from 250 replications of randomisation. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Unlike educational assortative matching, occupational assortative matching has decreased over time in all areas. Spatially, occupation assortative matching is higher in non-metropolitatan areas than metropolitan areas which is also contrary to the results from educational assortative matching. Apart from 1986, educational assortative matching is higher than occupational assortative matching in all areas. This result possibly reflects the diversity of economic opportunities in the metropolitan areas compared to non-metropolitan areas and is consistent with the co-location hypothesis of Costa and Kahn (2000). If cities solve the co-location problem of highly educated couples by offering more potential job matches, permiting specialisation and offering a wide range of economic activities, then we may expect education assortatitive matching to be higher than occupation assortative matching.

[38] The 1- digit classifies occupation into 9 categories - Legislators, Administrators and Managers; Professionals; Technicians and Associate Professionals; Clerks; Service and Sales Workers; Agriculture and Fishery Workers; Trades Workers; Plant and Machine Operators and Assemblers, and Elementary occupations (incl. Residual)

[39] In Appendix 16 and Appendix 17, we present the actual occupational parings for all urban areas respectively. Actual and random occupational pairings for Non-metropolitan areas are presented in Appendix 18 and Appendix 19 and Appendix 20 and 21 present the actual and random occupational areas for Metropolitan areas. Appendix 22,23 and 24 presents our assortative matching index for all urban areas, non-metropolitan areas, and metropolitan areas respectively

Given these results, in the next section, we link assortative matching to the income distribution and examine the implications of the patterns of assortative matching for income inequality from 1986 to 2013 and across areas.

4.4 The impact of assortative matching on income inequality among couples working full-time in New Zealand

In this section we examine what the patterns and trends in assortative matching discussed in the previous section imply for the distribution of income. Even when we find evidence that rates of educational assortative matching have not changed much, the effect on inequality might be different over time. Other factors like returns to education might interact with patterns of partnering and influence its implications for income inequality. For example, with increasing returns to education, the gap between high-educated couples and those with no education may increase even when the underlying patterns of assortative matching has not changed[40].

To show evidence of assortative matching on income inequality for male-female couples participating in the labour force, we compare the Mean Log Deviation (MLD) in the observed distribution to the MLD in the random counterfactual distribution. The Mean Log Deviation is defined as $\frac{1}{N}\sum_{i=1}^{N} ln\bar{x} - lnx_i$ in which N is the number of couples, $\bar{x}$ is the average income of all couples and x_i is the income of couple *i* (defined by the respective education levels of each partner and by their location). It is useful to note that *MLD* in invariant to the total number of couples if the relative frequencies remain constant and to the unit of measurement of income (e.g. nominal or real).

The MLDs for the random counterfactual distribution are average of 250 replications of randomisation with standard errors reported in brackets. For each census period and area, we simulate the randomisation 250 different times and report the average of the MLD from all the 250 different distributions. The standard errors are quite small and ranged from (0.02% to 0.04%). We can be confident on the estimated differences between the actual MLD and each of the counterfactual distributions. Our data is from the total population and not surveys like most other studies and this helps to pinpoint our estimates.

If inequality in the random distribution is lower (higher) than the actual distribution, this implies that the assortative matching is income inequality-increasing (inequality-reducing). Table 11 presents the results of the comparison of MLDs for the actual and random distribution for each area and in Figure 2 we plot the role of assortative matching over time (difference in MLDs between the actual and counterfactual random distribution).

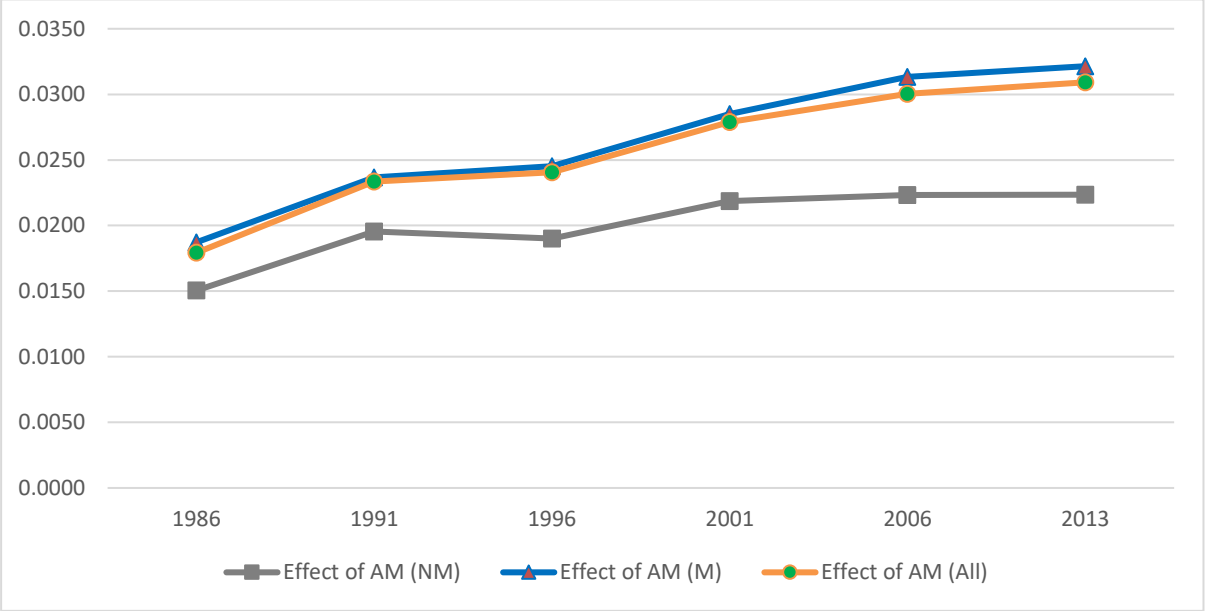
[40] Furthermore, assortative matching will have a multiplicative effect on household income. Percentage change in household income = percentage change in male income + percentage change in female income. When there is educational assortative matching and the rate of return to education increases, inequality in household income grows faster than inequality in individual income.

Table 11: Effect of educational assortative matching on the distribution of income of couples working full-time in each Census period by area: MLDs

25-64	1986	1991	1996	2001	2006	2013	Changes between 1986
Non-metropolitan							
Observed	0.083	0.099	0.103	0.112	0.110	0.109	30%
Unconditional randomisation	0.0685	0.0803	0.0844	0.0903	0.0889	0.0877	28%
Standard errors	(0.03%)	(0.04%)	(0.04%)	(0.03%)	(0.03%)	(0.03%)	
Effect of assortative matching (MLD points)	0.0152	0.0196	0.0195	0.0218	0.0220	0.0215	0.0063
Effect as a proportion of observed inequality	18%	20%	19%	19%	20%	20%	
Metropolitan							
Observed	0.0906	0.1093	0.1194	0.1298	0.1308	0.1372	51%
Unconditional randomisation	0.0719	0.0855	0.0948	0.1006	0.0992	0.1048	46%
Standard errors	(0.02%)	(0.02%)	(0.02%)	(0.02%)	(0.02%)	(0.02%)	
Effect of assortative matching (MLD points)	0.0187	0.0238	0.0246	0.0284	0.0316	0.0324	0.0137
Effect as a proportion of observed inequality	21%	22%	21%	22%	24%	24%	
All urban areas combined							
Observed	0.0895	0.1089	0.1179	0.1278	0.1285	0.1333	49%
Unconditional randomisation	0.0715	0.0854	0.0938	0.1000	0.0984	0.1026	44%
Standard errors	(0.02%)	(0.02%)	(0.02%)	(0.02%)	(0.02%)	(0.02%)	
Effect of assortative matching (MLD points)	0.0180	0.0235	0.0241	0.0278	0.0301	0.0307	0.0127
Effect as a proportion of observed inequality	20%	22%	21%	22%	23%	23%	

Notes: Results are the MLD measure of inequality for the actual and the randomised counterfactual distribution of income of couples working full-time in each census period. Standard errors in brackets and are the standard deviations from 250 replications of randomisation. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Figure 2: Effect of educational assortative matching on the distribution of income of couples working full-time in each Census period by area: MLDs



Notes: Figure 2 shows the difference between the MLD for the actual and the randomised counterfactual distribution. The difference represents the effect of assortativ ematching on the distribution of income. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Table 11 shows that assortative matching has a notable impact on income inequality. In all urban areas combined, the effect of assortative matching on income inequality in all period ranges from 0.0180 MLD points in 1986 to 0.0307 MLD points in 2013. To put in context, these numbers represent 20 percent of actual observed inequality in 1986 and 23 percent in 2013.

Reflecting the higher rates of assortative matching in metropolitan areas, it had a larger inequality-increasing impact in metropolitan areas than non-metropolitan areas. Also reflecting the increase in assortative in metropolitan areas between 1986 and 2013, the inequality-increasing effect also rose more in metropolitan areas than non-metropolitan areas. This is factor that has contributed to the growing differences in income inequality between metropolitan and non-metropolitan areas reported in earlier New Zealand research (e.g. Alimi et al. 2016).

Due to differences in measures of inequality, the MLD results are not directly comparable with evidence from the US and certain European countries in Eika et al. (2014) and Greenwood et al. (2014). These studies report smaller effects of assortative matching on inequality. Eika et al. (2014) found assortative matching contributed 2 percent in 1980 and 5 percent in 2007 while Greenwood (2014) reported the effect of assortative matching to be around 2 percent of actual inequality in both 1960 and 2005. Using Ginis as in these studies, we find that the

contribution of assortative matching in New Zealand ranges from 9 percent in 1986 to 11 percent of actual inequality in 2013.

Table 12 reports both Ginis and MLDs used to estimate the effect of assortative matching for all couples participating in the labour force i.e full-time, part-time and unemployed.

Table 12: Effect of educational assortative matching on the distribution of income of couples working full-time and everyone in the labour force Ginis and MLD

	1986	1991	1996	2001	2006	2013	Growth 1986-2013
Full-time (Gini)							
Actual	0.2261	0.2521	0.2655	0.2782	0.2761	0.2801	24%
Unconditional randomisation	0.2049	0.2266	0.2390	0.2485	0.2461	0.2503	22%
Effect of AM	0.0213	0.0258	0.0265	0.0298	0.03	0.0298	
Effect as a prop of actual	9%	10%	10%	11%	11%	11%	
All labour force (Gini)							
Actual	0.2677	0.3095	0.3159	0.3231	0.3193	0.3261	22%
Unconditional randomisation	0.2586	0.292	0.2876	0.2934	0.2958	0.3047	18%
Effect of AM	0.0091	0.0175	0.0283	0.0297	0.0235	0.0214	
Effect as a prop of actual	3%	6%	9%	9%	7%	7%	
All labour force (MLD)							
Actual	0.1216	0.1649	0.1719	0.1792	0.1815	0.1916	58%
Unconditional randomisation	0.1154	0.1491	0.1376	0.1425	0.1504	0.1606	39%
Effect of AM	0.0062	0.0158	0.0343	0.0366	0.0311	0.031	
Effect as a prop of actual	5%	10%	20%	20%	17%	16%	

Notes: Results are the Gini and MLD measure of inequality for the actual and the randomised distribution of income of couples working full-time and all labour force (full-time employed, part-time employed, and unemployed) in each census period.

Using the same measure of inequality, namely the Gini coefficient, the effect of assortative matching in New Zealand is greater than the US. This may be because we focus on the population working full-time while these other studies do not restrict the labour force status. We already show that within-group inequality is higher for those working full-time. Also, by focusing on those working full-time, we limit to some extent the effect of endogenous joint labour supply responses. Endogenous joint labour supply responses are likely to dampen the effect of assortative matching on inequality (see Pestel, 2017). Indeed when we do not restrict to those working full-time and focus on the total population aged 25 to 64 earning positive income, we find lower effects of assortative matching of between 3 and 7 percent using Ginis and 5 and 16

percent using Mean Log Deviations (see Table 12). The difference in the reference population between our studies and these studies means care needs to be taken before concluding that assortative matching contributes more to inequality in New Zealand than the US[41]. We know that partnering isn't entirely random and couples sort based on certain observable and unobservable characteristics. We account for sorting on these characteristics by preserving the actual distribution of these characteristics of couples in our randomised counterfactuals. We condition based on age, education, and location as well as combinations of these factors. For example, in our age-conditional randomisation, we preserve the age distribution of couples i.e. this counterfactual distribution is based on randomisation of partners but we partner people up with another random partner with the exact same age as their actual partner. In Table 13, we presents the results of the actual, unconditional, and the difference between the unconditional randomisation and each of the conditional randomisations. As with the descriptive statistics on randomisation, the randomisation results are the average of 250 replications of randomisation. The standard errors for these results are small and ranged from 0.01% to 0.04%, so we can be quite confident on the estimated differences between actual MLD and each of the counterfactual distributions.

[41] Greenwood et al. (2014) focused on singles and married couples aged 25-54 and Eika et al. (2014) focused on husband and wife couples earning positive income with mean age between 26 and 60 years.

Table 13: Effect of educational assortative matching on the distribution of income of couples working full-time under unconditional and conditional randomisations using MLDs by area

Non-metropolitan						
Distribution	**1986**	**1991**	**1996**	**2001**	**2006**	**2013**
Actual	0.0837	0.0999	0.1039	0.1121	0.1109	0.1092
Unconditional randomisation	0.0685	0.0803	0.0844	0.0903	0.0889	0.0877
Difference between the unconditional randomisation and conditional randomisation						
Age conditional	-0.0002	+0.0000	+0.0001	+0.0004	+0.0004	+0.0006
Education conditional	+0.0023	+0.0034	+0.0036	+0.0038	+0.0032	+0.0028
Age and Education conditional	+0.0024	+0.0037	+0.0041	+0.0045	+0.0041	+0.0042
Location conditional	+0.0005	+0.0007	+0.0007	+0.0008	+0.0006	+0.0007
Age, education and location conditional	+0.0037	+0.0055	+0.0061	+0.0064	+0.0058	+0.0060
Maximum Assortative Matching	+0.0364	+0.0533	+0.0399	+0.0465	+0.0393	+0.0370
Maximum disassortative matching	-0.0207	-0.0288	-0.0243	-0.0307	-0.0392	-0.0283
Metropolitan						
Distribution	**1986**	**1991**	**1996**	**2001**	**2006**	**2013**
Actual	0.0906	0.1093	0.1194	0.1290	0.1308	0.1372
Unconditional randomisation	0.0719	0.0855	0.0948	0.1006	0.0992	0.1048
Difference between the unconditional randomisation and conditional randomisation						
Age conditional	-0.0003	0.0000	+0.0001	+0.0002	+0.0004	+0.0011
Education conditional	+0.0035	+0.0050	+0.0050	+0.0047	+0.0039	+0.0041
Age and Education conditional	+0.0034	+0.0051	+0.0055	+0.0053	+0.0049	+0.0062
Location conditional	+0.0011	+0.0020	+0.0022	+0.0027	+0.0023	+0.0021
Age, education and location conditional	+0.0044	+0.0067	+0.0072	+0.0073	+0.0067	+0.0079
Maximum assortative matching	+0.0341	+0.0441	+0.0508	+0.0612	+0.0476	+0.0455
Maximum disassortative matching	-0.0229	-0.0324	-0.0320	-0.0341	-0.0277	-0.0326
All urban areas						
Distribution	**1986**	**1991**	**1996**	**2001**	**2006**	**2013**
Actual	0.0895	0.1089	0.1179	0.1278	0.1285	0.1333
Unconditional randomisation	0.0715	0.0854	0.0937	0.1000	0.0984	0.1026
Difference between the unconditional randomisation and conditional randomisation						
Age conditional	-0.0003	-0.0001	+0.0001	+0.0002	+0.0003	+0.0009
Education conditional	+0.0033	+0.0048	+0.0049	+0.0049	+0.0041	+0.0042
Age and Education conditional	+0.0033	+0.0050	+0.0054	+0.0055	+0.0050	+0.0061
Location conditional	+0.0013	+0.0025	+0.0027	+0.0033	+0.0028	+0.0026
Age, education and location conditional	+0.0045	+0.0072	+0.0078	+0.0082	+0.0074	+0.0083
Maximum assortative matching	+0.0352	+0.0472	+0.0484	+0.0584	+0.0463	+0.0443
Maximum disassortative matching	-0.0240	-0.0323	-0.0310	-0.0503	-0.0303	-0.0300

Notes: Results are the MLD measure of inequality for the actual and unconditional randomised distributions, and the difference in the MLD measure of the unconditional distribution and the conditional-randomised distribution. All distributions are for couples working full-time in each census period. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Our conditional randomisation indicates the role sorting on these observed characteristics play in inequality. We compare all conditional randomisations with the unconditional randomisation in each period. If the conditional randomisation results are higher than the unconditional randomisation, this implies that the observed pattern of sorting on this characteristic is inequality-increasing i.e. the way people sort on this characteristic increases inequality more than if sorting on this characteristics was random. Apart from a few exceptions in the age-conditional randomisation[42], in all variants of our conditional randomisation, inequality is higher in the conditional distributions than the purely random unconditional distribution. Hence, inequality increases when we preserve the observed distribution of these characteristics. The effects are smaller in non-metropolitan areas than metropolitan areas[43].

The conditional counterfactuals show that patterns of age sorting are almost always inequality-increasing in all periods and all areas. The exceptions are in in 1986. Unsurprisingly, patterns of sorting on education are inequality-increasing and larger in magnitude than age sorting in all areas. We also find that location is important, patterns of sorting on location is inequality-increasing and has bigger effects than age sorting but less than education sorting. In all urban areas, inequality in the counterfactual distribution that preserves the actual distribution of all three factors is around 85 percent of actual inequality in 1986 but 83 percent in 2013. This indicates that sorting on unobservable characteristics is also important and has become slightly more important over time.

Finally, we follow Kuhn and Ravazzini (2017) and consider two counterfactual distributions that assume extreme level of assortative matching. We sort individuals in couples based on our ordinal measure of education and income (income bands). In the maximum assortative matching counterfactual, we match the highest educated males in the highest income bands to females with the highest education in the highest income band, and so on. This gives us an estimate of what inequality would look like under extreme maximum assortative matching. Conversely, we match the highest educated-highest income males to the lowest educated-lowest-income females and so on for an estimate of maximum disassortative matching. The results show the potential of assortative matching with measures of inequality under the assumptions of maximum assortative matching are around double that under minimum assortative matching[44]. These are reported in the last 2 rows of the results by area in Table 13.

[42]In 1986 and 1991, patterns of age sorting are inequality-decreasing in all areas combined

[43] The only exception is in age randomisation in 2001

[44] Although actual inequality is closer to the results under maximum assortative matching than maximum disassortative matching, this effect isn't purely due to assortative matching as results under pure randomisation are closer to maximum assortative matching than maximum disassortative as well. The actual results are closer to maximum assortative matching than maximum disassortative because income does not follow a normal distribution but is rightly skewed (see Kuhn and Ravazzini, 2017).

5 Conclusion

The changes in the distribution of income in most western countries continue to receive considerable attention. While most of the focus has been on the role of economic variables, there is growing evidence that socio-demographic factors have been crucial as well.

One socio-demographic factor that is important to household income is the role of education assortative matching. Patterns of partnering will have a direct effect on household income. Early studies of assortative matching and popular opinion have suggested that there has been an increase in assortative matching over time, especially at the top of the educational distribution. In this chapter we examined the patterns of assortative matching for couples working full time in New Zealand. We find that rates of assortative matching have increased. However, and contrary to earlier evidence and popular discourse, assortative matching has fallen at the top and bottom of the educational distribution but increased in the middle (other-educated). Earlier studies of assortative matching often just took increases in correlation of levels of education between couples or changes in the proportion of couples with similar levels of education as evidence of assortative matching. These methods did not account for secular changes in the educational distribution and often failed to differentiate the impact of changes in educational distribution and changes in rates of assortative matching. Changes in educational distribution will influence the corrrelation of educational achievement between couples or observed proportions of couples with identical levels of education.

Accounting for secular changes in the distribution of education using a counterfactual randomisation approach, our study provides evidence from the New Zealand context. The New Zealand context is unique because, unlike the US and Europe, New Zealand has a combination of increasing inequality, increasing educational attainment but a low and falling educational premium. We take an accounting approach and link assortative matching to inequality.

Although our study did not account for all possible endogenous labour supply issues through formal modelling, we limit endogenous joint labour supply responses by focusing on those working full-time. We find that educational assortative matching has slightly increased in all urban areas and spatially, educational assortative matching is higher in metropolitan areas where it increased over the 1986 to 2013 period than in non-metropolitan areas where it decreased over this period.

We find that assortative matching has had a non-neglible effect on the distribution of total income of male-female couples in New Zealand. We go beyond the national level analysis of educational assortative matching in most studies and take a spatial approach. We find notable variation by area. Assortative matching and its impact on the distribution of income is larger and rose faster in metropolitan than non-metropolitan areas.

Finally, partnering is selective on certain observable and unobservable characteristics. We present evidence on the role of sorting on education, age and location and also by simulating extreme levels of assortative matching, we show that assortative matching has a large potential to affect the distribution of income.

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Appendix

Appendix Table A: Summary of MLD changes by area for the individual population 25-64. Source: Alimi et al. (2018)

Area	1986	1991	1996	2001	2006	2013	Percentage Change 1986-2013
Non-metropolitan	0.3589	0.3275	0.3340	0.3354	0.3065	0.3177	-11%
Metropolitan	0.3500	0.3415	0.3651	0.3719	0.3468	0.3656	4%
All urban area	0.3538	0.3402	0.3596	0.3664	0.3395	0.3565	1%

Notes: Results are the MLD measure of inequality for the individual population 25-64 in each census period. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Appendix Table B: Decomposition of personal income inequality by labour-force groups: Non-metropolitan areas

	1986	1991	1996	2001	2006	2013
Non-Metropolitan						
Between-group contributions						
Full-time	-0.1020	-0.1170	-0.1195	-0.1196	-0.1030	-0.1101
Part-time	0.1192	0.1136	0.1333	0.1377	0.1258	0.1237
Unemployed	0.0368	0.0644	0.0494	0.0463	0.0262	0.0427
Sum between-group	0.0540	0.0610	0.0632	0.0644	0.0490	0.0563
Between as a prop. of total	22.2%	24.1%	22.3%	22.8%	19.1%	21.4%
Within-group contributions						
Full-time	0.1155	0.1205	0.1399	0.1427	0.1371	0.1369
Part-time	0.0565	0.0543	0.0675	0.0636	0.0623	0.0558
Unemployed	0.0177	0.0176	0.0130	0.0116	0.0085	0.0141
Sum within-group	0.1897	0.1924	0.2204	0.2179	0.2079	0.2068
Full-time as a prop. of sum within-group	60.9%	62.6%	63.5%	65.5%	65.9%	66.2%
Total (sum between-group + sum within-group)	0.2437	0.2533	0.2836	0.2823	0.2570	0.2632
Sum within as prop of total-inequality	77.8%	76.0%	77.7%	77.2%	80.9%	78.6%

Notes: Results are the between and within-group contribution to overall inequality (as measured by the MLD) for those participating in the labour force in Non-metropolitan area (full-time employed, part-time employed and unemployed). Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Appendix Table C: Decomposition of personal income inequality by labour-force groups: Metropolitan areas

	1986	1991	1996	2001	2006	2013
Metropolitan						
Between-group contributions						
Full-time	-0.0909	-0.1037	-0.1080	-0.1066	-0.0916	-0.0994
Part-time	0.1066	0.0985	0.1157	0.1195	0.1094	0.1105
Unemployed	0.0342	0.0589	0.0522	0.0467	0.0263	0.0420
Sum between-group	0.0499	0.0537	0.0599	0.0596	0.0441	0.0531
Between as a prop. of total	21.1%	21.2%	19.9%	19.4%	15.6%	17.7%
Within-group contributions						
Full-time	0.1250	0.1323	0.1635	0.1721	0.1665	0.1721
Part-time	0.0462	0.0486	0.0622	0.0597	0.0610	0.0561
Unemployed	0.0150	0.0193	0.0160	0.0156	0.0113	0.0180
Sum within-group	0.1862	0.2002	0.2417	0.2474	0.2388	0.2462
Full-time as a prop. of sum within-group	67.1%	66.1%	67.6%	69.6%	69.7%	69.9%
Total (sum between-group + sum within-group)	0.2360	0.2539	0.3014	0.3068	0.2829	0.2992
Sum within as prop of total-inequality	78.9%	78.8%	80.2%	80.6%	84.4%	82.3%

Notes: Results are the between and within-group contribution to overall inequality (as measured by the MLD) for those participating in the labour force in Metropolitan area (full-time employed, part-time employed and unemployed). Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas.

Appendix Table D: Mean and inequality statistics by couple type in each census period for Non-metropolitan areas

	Non-metropolitan area					
1986	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$89,377			
Group mean	$136,930	$120,380	$94,538	$108,655	$83,943	$75,861
Rel. mean income	1.53	1.35	1.06	1.22	0.94	0.85
By-group MLD	0.0935	0.0879	0.0718	0.0940	0.0701	0.0747
Pop share	0.03	0.06	0.34	0.01	0.33	0.24
Overall MLD			0.0837			
1991	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$90,608			
Group mean	$146,973	$127,284	$92,719	$104,222	$82,086	$72,621
Rel. mean income	1.62	1.40	1.02	1.15	0.91	0.80
By-group MLD	0.0870	0.0962	0.0835	0.1144	0.0840	0.0864
Pop share	0.03	0.07	0.43	0.01	0.30	0.16
Overall MLD			0.0999			
1996	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$98,052			
Group mean	$150,843	$131,772	$98,790	$113,377	$87,925	$77,545
Rel. mean income	1.54	1.34	1.01	1.16	0.90	0.79
By-group MLD	0.1028	0.0984	0.0826	0.0971	0.0870	0.0929
Pop share	0.05	0.10	0.40	0.01	0.29	0.16
Overall MLD			0.1039			
2001	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$105,003			
Group mean	$163,771	$136,730	$102,986	$113,769	$90,356	$78,852
Rel. mean income	1.56	1.30	0.98	1.08	0.86	0.75
By-group MLD	0.1034	0.1079	0.0919	0.0942	0.0919	0.0945
Pop share	0.05	0.12	0.47	0.01	0.24	0.10
Overall MLD			0.1121			
2006	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$109,935			
Group mean	$159,717	$131,887	$107,087	$115,999	$93,743	$80,834
Rel. mean income	1.45	1.20	0.97	1.06	0.85	0.74
By-group MLD	0.1195	0.1040	0.0948	0.0898	0.0874	0.0914
Pop share	0.07	0.16	0.45	0.02	0.22	0.08
Overall MLD			0.1109			
2013	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$115,013			
Group mean	$160,884	$131,635	$108,024	$117,180	$96,166	$81,200
Rel. mean income	1.40	1.14	0.94	1.02	0.84	0.71
By-group MLD	0.1293	0.0991	0.0906	0.0811	0.0817	0.0894
Pop share	0.10	0.21	0.45	0.02	0.17	0.06
Overall MLD			0.1092			

Notes: Results are the mean, relative mean income, MLD and population share for each educational pair and the overall mean income in Non-metropolitan area in each census period. Abbreviations: HH- two high-educated partners; HO /OH - one high-educated partner and one other-educated partner; OO - two other-educated partners; HL/LH - one high-educated partner and one low-educated partner; OL /LO - one other-educated partner and one one low-educated partner; LL - two low-educated partners. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Appendix Table E: Mean and inequality statistics by couple type in each census period for Metropolitan areas

	Metropolitan area					
1986	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$98,123			
Group mean	$146,262	$128,585	$101,830	$116,695	$89,540	$78,372
Rel. mean income	1.49	1.31	1.04	1.19	0.91	0.80
By-group MLD	0.0883	0.0837	0.0776	0.0972	0.0711	0.0746
Pop share	5%	9%	36%	1%	29%	20%
Overall MLD			0.0906			
1991	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$105,307			
Group mean	$161,187	$138,226	$104,628	$121,044	$90,105	$76,946
Rel. mean income	1.53	1.31	0.99	1.15	0.86	0.73
By-group MLD	0.0996	0.0944	0.0902	0.1108	0.0834	0.0851
Pop share	7%	11%	44%	1%	25%	12%
Overall MLD			0.1093			
1996	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$115,835			
Group mean	$166,467	$144,208	$113,324	$127,910	$97,737	$82,283
Rel. mean income	1.44	1.24	0.98	1.10	0.84	0.71
By-group MLD	0.1264	0.1093	0.0931	0.1211	0.0910	0.0904
Pop share	10%	14%	39%	2%	23%	13%
Overall MLD			0.1194			
2001	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$126,080			
Group mean	$177,091	$151,851	$117,628	$132,544	$101,115	$85,073
Rel. mean income	1.40	1.20	0.93	1.05	0.80	0.67
By-group MLD	0.1286	0.1180	0.1074	0.1179	0.0916	0.0937
Pop share	12%	18%	45%	1%	17%	7%
Overall MLD			0.1290			
2006	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$130,388			
Group mean	$168,878	$148,034	$120,148	$129,836	$104,688	$84,979
Rel. mean income	1.30	1.14	0.92	1.00	0.80	0.65
By-group MLD	0.1367	0.1175	0.1119	0.1077	0.0950	0.1004
Pop share	16%	22%	40%	2%	14%	5%
Overall MLD			0.1308			
2013	HH	HO/OH	OO	HL/LH	OL/LO	LL
Overall mean			$136,938			
Group mean	$174,369	$148,711	$121,162	$126,143	$103,775	$82,778
Rel. mean income	1.27	1.09	0.88	0.92	0.76	0.60
By-group MLD	0.1401	0.1212	0.1150	0.1038	0.0933	0.1119
Pop share	22%	26%	37%	2%	10%	3%
Overall MLD			0.1372			

Notes: Results are the mean, relative mean income, MLD and population share for each educational pair and the overall mean income in Non-metropolitan area in each census period. Abbreviations: HH- two high-educated partners; HO /OH - one high-educated partner and one other-educated partner; OO - two other-educated partners; HL/LH - one high-educated partner and one low-educated partner; OL /LO - one other-educated partner and one one low-educated partner; LL - two low-educated partners. Metropolitan areas are the six largest New Zealand cities (in order of size): Auckland, Wellington, Christchurch, Hamilton, Tauranga and Dunedin. All other urban areas are considered non-metropolitan areas

Appendix Table F: Educational distribution for individuals in couples aged 25-64 in Non-metropolitan areas from 1986 to 2013

Educational distribution: Non- Metropolitan areas							
	Total	**Prop.**	**Male**	**Prop.**	**Female**	**Prop.**	**Ratio of**
			1986				
High-Education	3,990	6%	2,502	7%	1,491	4%	168%
Other-Education	35,697	53%	18,393	55%	17,304	52%	106%
Low-Education	27,123	41%	12,513	37%	14,610	44%	86%
Total specified	66,813	100%	33,408	100%	33,408	100%	
			1991				
High-Education	5,067	7%	2,937	8%	2,130	6%	138%
Other-Education	42,975	61%	21,336	61%	21,636	62%	99%
Low-Education	22,185	32%	10,839	31%	11,346	32%	96%
Total specified	70,224	100%	35,112	100%	35,112	100%	
			1996				
High-Education	6,693	10%	3,669	11%	3,021	9%	121%
Other-Education	38,637	59%	18,435	56%	20,202	61%	91%
Low-Education	20,523	31%	10,821	33%	9,699	29%	112%
Total specified	65,850	100%	32,925	100%	32,928	100%	
			2001				
High-Education	9,135	12%	4,410	12%	4,725	13%	93%
Other-Education	49,047	65%	23,649	63%	25,398	67%	93%
Low-Education	17,286	23%	9,678	26%	7,611	20%	127%
Total specified	75,468	100%	37,734	100%	37,734	100%	
			2006				
High-Education	15,894	16%	6,720	14%	9,174	19%	73%
Other-Education	62,700	64%	31,407	64%	31,296	64%	100%
Low-Education	19,797	20%	11,070	23%	8,727	18%	127%
Total specified	98,391	100%	49,197	100%	49,194	100%	
			2013				
High-Education	21,042	22%	7,878	16%	13,164	27%	60%
Other-Education	61,863	63%	32,343	66%	29,520	61%	110%
Low-Education	14,547	15%	8,505	17%	6,039	12%	141%
Total specified			48,726	100%	48,726	100%	

Notes: Results are the number and proportion by gender in each educational group in Non-metropolitan area for each census period. High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Appendix Table G: Educational distribution for individuals in couples aged 25-64 in Metropolitan areas from 1986 to 2013

	Educational distribution: Metropolitan area						
	Total	**Prop.**	**Male**	**Prop.**	**Female**	**Prop.**	**Ratio of**
			1986				
High-Education	16,920	10%	10,086	12%	6,837	8%	148%
Other-Education	95,274	55%	49,092	56%	46,182	53%	106%
Low-Education	61,779	36%	27,810	32%	33,969	39%	82%
Total specified	173,973	100%	86,988	100%	86,988	100%	
			1991				
High-Education	23,694	13%	13,395	14%	10,299	11%	130%
Other-Education	114,162	62%	57,135	62%	57,027	62%	100%
Low-Education	46,944	25%	21,870	24%	25,074	27%	87%
Total specified	184,797	100%	92,400	100%	92,400	100%	
			1996				
High-Education	32,805	18%	17,616	19%	15,186	17%	116%
Other-Education	105,153	57%	51,147	56%	54,006	59%	95%
Low-Education	45,231	25%	22,830	25%	22,404	24%	102%
Total specified	183,189	100%	91,596	100%	91,596	100%	
			2001				
High-Education	49,419	22%	24,489	21%	24,933	22%	98%
Other-Education	142,806	62%	70,233	61%	72,573	63%	97%
Low-Education	36,552	16%	19,665	17%	16,887	15%	116%
Total specified	228,777	100%	114,390	100%	114,390	100%	
			2006				
High-Education	84,228	28%	38,706	26%	45,519	31%	85%
Other-Education	174,237	58%	88,857	60%	85,383	57%	104%
Low-Education	39,468	13%	21,405	14%	18,063	12%	119%
Total specified	297,933	100%	148,968	100%	148,968	100%	
			2013				
High-Education	111,813	36%	48,393	31%	63,420	40%	76%
Other-Education	174,120	55%	92,373	59%	81,747	52%	113%
Low-Education	28,803	9%	16,602	11%	12,201	8%	136%
Total specified	314,736	100%	157,368	100%	157,368	100%	

Notes: Results are the number and proportion by gender in each educational group in Metropolitan area for each census period, High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Appendix Table H: Actual proportion of couples in each educational pairing: Non-metropolitan areas

Actual proportion - Non-metropolitan			
Female	**Male**		
	High-Education	Other-Education	Low-Education
1986			
High-Education	2.5%	1.6%	0.3%
Other-Education	4.4%	34.0%	13.4%
Low-Education	0.5%	19.5%	23.8%
1991			
High-Education	3.3%	2.5%	0.3%
Other-Education	4.8%	42.6%	14.2%
Low-Education	0.3%	15.7%	16.3%
1996			
High-Education	4.7%	3.8%	0.6%
Other-Education	5.8%	39.6%	16.0%
Low-Education	0.6%	12.6%	16.3%
2001			
High-Education	5.3%	6.4%	0.9%
Other-Education	6.0%	46.8%	14.5%
Low-Education	0.4%	9.5%	10.3%
2006			
High-Education	7.2%	9.9%	1.5%
Other-Education	6.1%	44.8%	12.8%
Low-Education	0.4%	9.1%	8.3%
2013			
High-Education	9.9%	15.2%	1.9%
Other-Education	5.9%	44.6%	10.1%
Low-Education	0.3%	6.6%	5.5%

Notes: Results are the proportion of male-female couples in each educational pairing in Non-metropolitan area for each census period. High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Appendix Table I: Proportion of couples in each educational pairing under randomisation: Non-metropolitan areas

Randomised - Non-metropolitan			
Female	**Male**		
	High-Education	Other-Education	Low-Education
1986			
High-Education	0.3% (0.0003)	2.4% (0.0006)	1.7% (0.0005)
Other-Education	3.9% (0.0007)	28.5% (0.0013)	19.4% (0.0013)
Low-Education	3.3% (0.0008)	24.1% (0.0013)	16.4% (0.0013)
1991			
High-Education	0.5% (0.0003)	3.7% (0.0007)	1.9% (0.0006)
Other-Education	5.2% (0.0007)	37.4% (0.0012)	19.0% (0.0011)
Low-Education	2.7% (0.0006)	19.6% (0.0012)	10.0% (0.0010)
1996			
High-Education	1.0% (0.0005)	5.1% (0.0008)	3.0% (0.0008)
Other-Education	6.8% (0.0009)	34.4% (0.0013)	20.2% (0.0013)
Low-Education	3.3% (0.0008)	16.5% (0.0013)	9.7% (0.0012)
2001			
High-Education	1.5% (0.0005)	7.9% (0.0008)	3.2% (0.0007)
Other-Education	7.9% (0.0008)	42.2% (0.0011)	17.3% (0.0010)
Low-Education	2.4% (0.0007)	12.6% (0.0009)	5.2% (0.0008)
2006			
High-Education	2.5% (0.0006)	11.9% (0.0008)	4.2% (0.0007)
Other-Education	8.7% (0.0007)	40.6% (0.0010)	14.3% (0.0009)
Low-Education	2.4% (0.0006)	11.3% (0.0008)	4.0% (0.0007)
2013			
High-Education	4.4% (0.0007)	17.9% (0.0009)	4.7% (0.0008)
Other-Education	9.8% (0.0008)	40.2% (0.0011)	10.6% (0.0009)
Low-Education	2.0% (0.0005)	8.2% (0.0007)	2.2% (0.0006)

Notes: Results are the proportion of male-female couples in Non-metropolitan area in each educational pairing in each census period under randomised matching. High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification.

Appendix Table J: Actual proportion of couples in each educational pairing: Metropolitan areas

Female	Actual proportion - Metropolitan Male		
	High-Education	Other-Education	Low-Education
1986			
High-Education	4.6%	2.9%	0.4%
Other-Education	6.3%	35.5%	11.2%
Low-Education	0.7%	18.0%	20.3%
1991			
High-Education	6.6%	4.1%	0.5%
Other-Education	7.4%	43.6%	10.8%
Low-Education	0.5%	14.2%	12.5%
1996			
High-Education	10.0%	5.9%	0.7%
Other-Education	8.5%	38.9%	11.6%
Low-Education	0.8%	11.0%	12.6%
2001			
High-Education	11.7%	9.3%	0.8%
Other-Education	9.2%	44.8%	9.4%
Low-Education	0.5%	7.3%	7.0%
2006			
High-Education	16.5%	13.0%	1.1%
Other-Education	9.1%	40.4%	7.8%
Low-Education	0.4%	6.3%	5.4%
2013			
High-Education	21.5%	17.4%	1.3%
Other-Education	8.9%	37.2%	5.8%
Low-Education	0.3%	4.0%	3.4%

Notes: Results are the actual proportion of male-female couples in each educational pairing in Metropolitan area for each census period. High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification.

Appendix Table K: Proportion of couples in each educational pairing under randomisation: Metropolitan areas

Randomised - Metropolitan			
Female	**Male**		
	High-Education	Other-Education	Low-Education
1986			
High-Education	0.9% (0.0003)	4.4% (0.0004)	2.5% (0.0004)
Other-Education	6.2% (0.0006)	30.0% (0.0008)	17.0% (0.0007)
Low-Education	4.5% (0.0005)	22.0% (0.0008)	12.5% (0.0007)
1991			
High-Education	1.6% (0.0004)	6.9% (0.0005)	2.6% (0.0005)
Other-Education	8.9% (0.0005)	38.2% (0.0008)	14.6% (0.0007)
Low-Education	3.9% (0.0005)	16.8%(0.0007)	6.4% (0.0006)
1996			
High-Education	3.2% (0.0005)	9.3% (0.0006)	4.1% (0.0006)
Other-Education	11.3% (0.0007)	32.9% (0.0008)	14.7% (0.0007)
Low-Education	4.7% (0.0006)	13.7% (0.0007)	6.1% (0.0006)
2001			
High-Education	4.7% (0.0005)	13.4% (0.0006)	3.7% (0.0005)
Other-Education	13.6% (0.0006)	39.0% (0.0007)	10.9% (0.0005)
Low-Education	3.2% (0.0004)	9.1% (0.0005)	2.5% (0.0004)
2006			
High-Education	7.9% (0.0006)	18.2% (0.0006)	4.4% (0.0005)
Other-Education	14.9% (0.0006)	34.2% (0.0006)	8.2% (0.0005)
Low-Education	3.1% (0.0004)	7.2% (0.0004)	1.7% (0.0003)
2013			
High-Education	12.4% (0.0006)	23.7% (0.0007)	4.3% (0.0004)
Other-Education	16.0% (0.0006)	30.5% (0.0007)	5.5% (0.0004)
Low-Education	2.4% (0.0003)	4.6% (0.0003)	0.8% (0.0002)

Notes: Results are the proportion of male-female couples in Metropolitan areas in each educational pairing in each census period under randomised matching. High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Appendix Table L: Concentration ratio from 1986 to 2013: Non-metropolitan areas

	Concentration ratio		
	High-Education	Other-Education	Low-Education
1986			
High-Education	7.5	0.7	0.2
Other-Education	1.1	1.2	0.7
Low-Education	0.2	0.8	1.5
1991			
High-Education	6.4	0.7	0.2
Other-Education	0.9	1.1	0.7
Low-Education	0.1	0.8	1.6
1996			
High-Education	4.6	0.7	0.2
Other-Education	0.9	1.2	0.8
Low-Education	0.2	0.8	1.7
2001			
High-Education	3.6	0.8	0.3
Other-Education	0.8	1.1	0.8
Low-Education	0.2	0.8	2.0
2006			
High-Education	2.8	0.8	0.4
Other-Education	0.7	1.1	0.9
Low-Education	0.2	0.8	2.1
2013			
High-Education	2.3	0.8	0.4
Other-Education	0.6	1.1	1.0
Low-Education	0.1	0.8	2.5

Notes: Results are the concentratio ratio i.e. ratio of actual proportion to random proportion of male-female couples in each educational group in each census period for Non-metropolitan areas. High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Appendix Table M: Concentration ratio from 1986 to 2013: Metropolitan areas

	Concentration ratio		
	High-Education	Other-Education	Low-Education
	1986		
High-Education	5.0	0.7	0.2
Other-Education	1.0	1.2	0.7
Low-Education	0.2	0.8	1.6
	1991		
High-Education	4.1	0.6	0.2
Other-Education	0.8	1.1	0.7
Low-Education	0.1	0.8	1.9
	1996		
High-Education	3.1	0.6	0.2
Other-Education	0.8	1.2	0.8
Low-Education	0.2	0.8	2.1
	2001		
High-Education	2.5	0.7	0.2
Other-Education	0.7	1.2	0.9
Low-Education	0.1	0.8	2.8
	2006		
High-Education	2.1	0.7	0.3
Other-Education	0.6	1.2	0.9
Low-Education	0.1	0.9	3.1
	2013		
High-Education	1.7	0.7	0.3
Other-Education	0.6	1.2	1.1
Low-Education	0.1	0.9	4.2

Notes: Results are the concentratio ratio i.e. ratio of actual proportion to random proportion of male-female couples in each educational group in each census period for Metropolitan areas. High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Appendix Table N: Assortative matching index by educational group for non-metropolitan areas

	Non-metropolitan		
	High-Education	Other-Education	Low-Education
	1986		
High-Education	0.53	-0.41	-0.50
	(0.4%)	(3.9%)	(2.9%)
Other-Education	0.16	0.23	-0.33
	(1.7%)	(0.4%)	(1.0%)
Low-Education	-0.66	-0.23	0.35
	(3.0%)	(0.8%)	(0.4%)
	1991		
High-Education	0.50	-0.52	-0.37
	(0.3%)	(4.1%)	(1.9%)
Other-Education	-0.13	0.22	-0.40
	(2.4%)	(0.4%)	(1.3%)
Low-Education	-0.42	-0.31	0.30
	(1.6%)	(1.2%)	(0.3%)
	1996		
High-Education	0.46	-0.32	-0.39
	(0.3%)	(2.6%)	(1.7%)
Other-Education	-0.23	0.24	-0.33
	(2.5%)	(0.5%)	(1.3%)
Low-Education	-0.34	-0.30	0.33
	2001		
High-Education	0.37	-0.31	-0.25
	(0.3%)	(2.2%)	(0.9%)
Other-Education	-0.48	0.22	-0.33
	(3.0%)	(0.4%)	(1.6%)
Low-Education	-0.21	-0.42	0.34
	(0.9%)	(1.8%)	(0.4%)
	2006		
High-Education	0.42	-0.29	-0.19
	(0.3%)	(1.5%)	(0.6%)
Other-Education	-0.53	0.18	-0.19
	(2.3%)	(0.4%)	(1.3%)
Low-Education	-0.18	-0.35	0.31
	(0.6%)	(1.6%)	(0.3%)
	2013		
High-Education	0.47	-0.30	-0.22
	(0.3%)	(1.3%)	(0.8%)
Other-Education	-0.61	0.21	-0.08
	(2.1%)	(0.4%)	(1.4%)
Low-Education	-0.16	-0.39	0.33
	(0.6%)	(2.3%)	(0.4%)

Notes: Results are the educational assortative matching index calculated as $\frac{Actual-Random}{Max\ homogamy-Random}$ for each educational pairing for Non-metropolitan areas in each census period. Standard errors in brackets (standard errors are the standard deviations from 250 replications of randomisation). High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Appendix Table O: Assortative matching index by educational group for metropolitan areas

	Metropolitan		
	High-Education	Other-Education	Low-Education
	1986		
High-Education	0.53	-0.45	-0.40
	(0.2%)	(1.9%)	(1.1%)
Other-Education	0.03	0.24	-0.38
	(1.0%)	(0.3%)	(0.7%)
Low-Education	-0.54	-0.24	0.40
	(1.1%)	(0.6%)	(0.2%)
	1991		
High-Education	0.52	-0.66	-0.26
	(0.2%)	(2.0%)	(0.7%)
Other-Education	-0.28	0.23	-0.43
	(1.3%)	(0.2%)	(1.1%)
Low-Education	-0.32	-0.25	0.35
	(0.6%)	(0.8%)	(0.2%)
	1996		
High-Education	0.51	-0.46	-0.27
	(0.2%)	(1.3%)	(0.6%)
Other-Education	-0.36	0.26	-0.31
	(1.1%)	(0.3%)	(0.9%)
Low-Education	-0.27	-0.24	0.36
	(0.5%)	(0.8%)	(0.2%)
	2001		
High-Education	0.42	-0.49	-0.22
	(0.2%)	(1.1%)	(0.4%)
Other-Education	-0.56	0.26	-0.24
	(1.1%)	(0.2%)	(1.0%)
Low-Education	-0.23	-0.31	0.37
	(0.5%)	(1.2%)	(0.2%)
	2006		
High-Education	0.47	-0.43	-0.33
	(0.2%)	(0.7%)	(0.6%)
Other-Education	-0.52	0.27	-0.07
	(0.8%)	(0.2%)	(0.8%)
Low-Education	-0.30	-0.19	0.35
	(0.6%)	(1.1%)	(0.2%)
	2013		
High-Education	0.50	-0.37	-0.46
	(0.2%)	(0.5%)	(0.9%)
Other-Education	-0.48	0.31	0.06
	(0.6%)	(0.2%)	(0.7%)
Low-Education	-0.39	-0.17	0.38
	(0.8%)	(1.2%)	(0.2%)

Notes: Results are the educational assortative matching index calculated as $\frac{Actual-Random}{Max\ homogamy-Random}$ for each educational pairing for Metropolitan areas in each census period. Standard errors in brackets (standard errors are the standard deviations from 250 replications of randomisation). High-Education represent those with Bachelors degree and above, Other-Education are those with other forms of qualification but below the Bachelor level, and Low-Education are those with those with no qualification

Abbreviations for 1999 New Zealand Standard Occupational Classification:

- AD&M – Legislators, Administrators and Managers
- PROF - Professionals
- TECH – Technicians and Associate Professionals
- CLERKS - Clerks
- S&S – Service and Sales Workers
- AGRI - Agriculture and Fishery Workers
- TRADE – Trades Workers
- P&M – Plant and Machine Operators and Assemblers
- ELMT – Elementary occupations (incl. Residual)

Appendix Table P: Actual occupational pairings in 1986 and 2013: All urban areas

Female	**Actual occupational pairings- All urban areas** **Male**								
	AD&M	PROF	TECH	CLERKS	S & S	AGRI	TRADE	P&M	ELMT
				1986					
AD&M	5.0%	0.8%	0.9%	0.6%	0.6%	0.2%	1.3%	0.7%	0.4%
PROF	2.3%	5.3%	2.2%	1.3%	1.1%	0.3%	2.0%	1.0%	0.6%
TECH	1.2%	1.4%	1.7%	0.8%	0.6%	0.2%	1.3%	0.7%	0.4%
CLERKS	5.3%	3.2%	4.2%	3.6%	2.8%	0.7%	6.7%	3.2%	2.0%
S & S	1.7%	0.8%	1.3%	1.2%	1.9%	0.4%	2.9%	2.3%	1.4%
AGRI	0.1%	0.1%	0.1%	0.1%	0.1%	1.4%	0.2%	0.3%	0.1%
TRADE	0.2%	0.1%	0.2%	0.2%	0.1%	0.1%	0.9%	0.5%	0.2%
P&M	0.5%	0.2%	0.5%	0.7%	0.6%	0.3%	2.1%	2.6%	1.2%
ELMT	0.4%	0.2%	0.3%	0.5%	0.4%	0.2%	1.2%	1.5%	1.2%
				2013					
AD&M	7.3%	3.1%	2.5%	0.8%	1.5%	0.4%	2.5%	1.4%	1.4%
PROF	5.6%	7.9%	3.7%	1.2%	1.9%	0.5%	3.1%	1.6%	1.8%
TECH	3.4%	2.7%	2.8%	0.8%	1.3%	0.3%	2.2%	1.4%	1.3%
CLERKS	3.5%	2.2%	2.1%	1.1%	1.2%	0.3%	2.6%	1.7%	1.4%
S & S	1.8%	1.0%	1.2%	0.5%	1.8%	0.3%	1.8%	1.5%	1.1%
AGRI	0.1%	0.1%	0.1%	0.0%	0.0%	0.4%	0.1%	0.1%	0.1%
TRADE	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%	0.3%	0.1%	0.1%
P&M	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.4%	0.7%	0.3%
ELMT	0.7%	0.5%	0.4%	0.2%	0.3%	0.1%	0.7%	0.8%	1.1%

Notes: Results are the actual proportion of male-female couples in each occupational pairing for all urban areas combined in 1986 and 2013. Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Appendix Table Q: Occupational pairing under randomisation in 1986 and 2013: All urban areas

Female	Occupational pairing under randomisation- All urban areas Male								
	AD&M	PROF	TECH	CLERKS	S & S	AGRI	TRADE	P&M	ELMT
					1986				
AD&M	1.8%	1.3%	1.2%	0.9%	0.9%	0.4%	1.9%	1.3%	0.8%
PROF	2.7%	2.0%	1.8%	1.4%	1.3%	0.6%	3.0%	2.0%	1.2%
TECH	1.4%	1.0%	1.0%	0.7%	0.7%	0.3%	1.5%	1.1%	0.6%
CLERKS	5.3%	3.9%	3.6%	2.8%	2.6%	1.2%	5.8%	4.0%	2.4%
S & S	2.3%	1.7%	1.6%	1.2%	1.2%	0.5%	2.6%	1.8%	1.1%
AGRI	0.4%	0.3%	0.3%	0.2%	0.2%	0.1%	0.5%	0.3%	0.2%
TRADE	0.4%	0.3%	0.3%	0.2%	0.2%	0.1%	0.5%	0.3%	0.2%
P&M	1.5%	1.1%	1.0%	0.8%	0.7%	0.3%	1.6%	1.1%	0.7%
ELMT	1.0%	0.7%	0.7%	0.5%	0.5%	0.2%	1.0%	0.7%	0.4%
					2013				
AD&M	4.7%	3.7%	2.7%	1.0%	1.7%	0.5%	2.8%	1.9%	1.8%
PROF	6.2%	4.8%	3.6%	1.3%	2.3%	0.7%	3.7%	2.5%	2.3%
TECH	3.7%	2.8%	2.1%	0.8%	1.3%	0.4%	2.2%	1.5%	1.4%
CLERKS	3.6%	2.8%	2.1%	0.8%	1.3%	0.4%	2.2%	1.5%	1.4%
S & S	2.5%	1.9%	1.4%	0.5%	0.9%	0.3%	1.5%	1.0%	0.9%
AGRI	0.2%	0.2%	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%
TRADE	0.2%	0.1%	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%
P&M	0.5%	0.4%	0.3%	0.1%	0.2%	0.1%	0.3%	0.2%	0.2%
ELMT	1.1%	0.9%	0.6%	0.2%	0.4%	0.1%	0.7%	0.4%	0.4%

Notes: Results are the proportion of male-female couples in each occupational pairing under randomised matching in all urban areas combined in 1986 and 2013. Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Appendix Table R: Actual occupational pairings in 1986 and 2013: Non-metropolitan areas

Female	Actual occupational pairing - Non-metropolitan areas Male								
	AD&M	PROF	TECH	Clerks	S & S	AGRI	TRADE	P&M	ELMT
1986									
AD&M	5.4%	0.6%	0.8%	0.5%	0.6%	0.3%	1.3%	0.9%	0.4%
PROF	1.9%	5.2%	2.0%	1.1%	1.1%	0.6%	2.2%	1.3%	0.7%
TECH	0.8%	1.2%	1.5%	0.6%	0.6%	0.3%	1.3%	0.9%	0.5%
Clerks	4.2%	2.7%	3.5%	2.6%	2.5%	1.1%	6.4%	3.7%	1.7%
S & S	1.7%	0.9%	1.5%	1.3%	2.2%	0.9%	3.6%	3.3%	1.7%
AGRI	0.2%	0.2%	0.2%	0.1%	0.2%	2.3%	0.4%	0.6%	0.3%
TRADE	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.7%	0.3%	0.1%
P&M	0.4%	0.2%	0.4%	0.5%	0.6%	0.5%	1.9%	2.7%	1.0%
ELMT	0.4%	0.1%	0.3%	0.4%	0.3%	0.4%	1.0%	1.5%	1.0%
2013									
AD&M	6.3%	1.9%	2.1%	0.5%	1.6%	0.8%	2.8%	1.9%	1.6%
PROF	4.2%	5.6%	2.9%	0.8%	2.2%	1.1%	3.6%	2.3%	1.9%
TECH	2.7%	1.8%	2.1%	0.6%	1.3%	0.7%	2.6%	1.9%	1.3%
Clerks	3.3%	1.6%	1.9%	0.8%	1.2%	0.7%	3.1%	2.3%	1.5%
S & S	2.0%	0.8%	1.2%	0.5%	2.1%	0.8%	2.5%	2.3%	1.5%
AGRI	0.2%	0.1%	0.1%	0.0%	0.1%	0.8%	0.2%	0.2%	0.2%
TRADE	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%	0.3%	0.1%	0.1%
P&M	0.2%	0.1%	0.2%	0.1%	0.1%	0.2%	0.4%	1.0%	0.4%
ELMT	0.6%	0.4%	0.3%	0.2%	0.3%	0.3%	0.7%	1.1%	1.2%

Notes: Results are the actual proportion of male-female couples in each occupational pairing for Non-metropolitan areas in 1986 and 2013. Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Appendix Table S: Occupational pairing under randomisation in 1986 and 2013: Non-metropolitan areas

Occupational pairing under randomisation- Non-metropolitan areas									
Female	**Male**								
1986									
	AD&M	PROF	TECH	Clerks	S & S	AGRI	TRADE	P&M	ELMT
AD&M	1.7%	1.2%	1.1%	0.8%	0.9%	0.7%	2.0%	1.7%	0.8%
PROF	2.5%	1.8%	1.7%	1.2%	1.3%	1.1%	3.0%	2.5%	1.2%
TECH	1.2%	0.8%	0.8%	0.6%	0.6%	0.5%	1.4%	1.1%	0.6%
Clerks	4.3%	3.2%	2.9%	2.1%	2.3%	1.9%	5.3%	4.3%	2.1%
S & S	2.6%	1.9%	1.8%	1.3%	1.4%	1.1%	3.2%	2.6%	1.3%
AGRI	0.7%	0.5%	0.5%	0.3%	0.4%	0.3%	0.8%	0.7%	0.3%
TRADE	0.3%	0.2%	0.2%	0.1%	0.1%	0.1%	0.3%	0.3%	0.1%
P&M	1.3%	0.9%	0.9%	0.6%	0.7%	0.5%	1.5%	1.2%	0.6%
ELMT	0.8%	0.6%	0.5%	0.4%	0.4%	0.3%	1.0%	0.8%	0.4%
2013									
AD&M	3.8%	2.4%	2.1%	0.7%	1.8%	1.1%	3.2%	2.6%	1.9%
PROF	4.8%	3.0%	2.7%	0.9%	2.2%	1.3%	4.0%	3.2%	2.4%
TECH	3.0%	1.9%	1.6%	0.5%	1.4%	0.8%	2.5%	2.0%	1.5%
Clerks	3.2%	2.1%	1.8%	0.6%	1.5%	0.9%	2.7%	2.2%	1.6%
S & S	2.7%	1.7%	1.5%	0.5%	1.2%	0.7%	2.2%	1.8%	1.3%
AGRI	0.4%	0.2%	0.2%	0.1%	0.2%	0.1%	0.3%	0.3%	0.2%
TRADE	0.2%	0.1%	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%
P&M	0.5%	0.3%	0.3%	0.1%	0.2%	0.1%	0.4%	0.3%	0.3%
ELMT	1.0%	0.6%	0.6%	0.2%	0.5%	0.3%	0.8%	0.7%	0.5%

Notes: Results are the proportion of male-female couples in each occupational pairing under randomised matching in Non-metropolitan area in 1986 and 2013. Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Appendix Table T: Actual occupational pairings in 1986 and 2013: Metropolitan areas

Actual occupational pairing - Metropolitan areas									
Female	**Male**								
1986									
1986	AD&M	PROF	TECH	Clerks	S & S	AGRI	TRADE	P&M	ELMT
AD&M	4.9%	0.9%	1.0%	0.6%	0.6%	0.1%	1.3%	0.6%	0.4%
PROF	2.4%	5.3%	2.2%	1.3%	1.2%	0.2%	1.8%	0.8%	0.6%
TECH	1.4%	1.5%	1.8%	0.8%	0.7%	0.1%	1.4%	0.6%	0.4%
Clerks	5.8%	3.4%	4.5%	3.9%	3.0%	0.5%	6.7%	3.0%	2.1%
S & S	1.7%	0.8%	1.3%	1.2%	1.8%	0.3%	2.6%	1.9%	1.2%
AGRI	0.1%	0.1%	0.1%	0.1%	0.1%	1.0%	0.2%	0.1%	0.1%
TRADE	0.3%	0.1%	0.2%	0.2%	0.2%	0.0%	1.0%	0.5%	0.3%
P&M	0.5%	0.3%	0.5%	0.7%	0.6%	0.2%	2.1%	2.6%	1.3%
ELMT	0.3%	0.2%	0.3%	0.5%	0.4%	0.2%	1.3%	1.5%	1.2%
2013									
AD&M	7.6%	3.4%	2.7%	0.8%	1.5%	0.3%	2.4%	1.2%	1.3%
PROF	6.1%	8.6%	4.0%	1.3%	1.9%	0.4%	2.9%	1.4%	1.7%
TECH	3.6%	2.9%	3.1%	0.9%	1.3%	0.2%	2.1%	1.2%	1.2%
Clerks	3.6%	2.3%	2.1%	1.1%	1.2%	0.2%	2.4%	1.5%	1.4%
S & S	1.8%	1.0%	1.1%	0.5%	1.7%	0.2%	1.6%	1.2%	0.9%
AGRI	0.1%	0.1%	0.1%	0.0%	0.0%	0.3%	0.1%	0.1%	0.0%
TRADE	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%	0.3%	0.1%	0.1%
P&M	0.2%	0.1%	0.1%	0.1%	0.1%	0.0%	0.4%	0.6%	0.3%
ELMT	0.7%	0.6%	0.4%	0.2%	0.3%	0.1%	0.6%	0.7%	1.1%

Notes: Results are the actual proportion of male-female couples in each occupational pairing in Metropolitan areas in 1986 and 2013. Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Appendix Table U: Occupational pairing under randomisation in 1986 and 2013: Metropolitan areas

Occupational pairing under randomisation- Metropolitan areas									
Female	**Male**								
1986									
	AD&M	PROF	TECH	Clerks	S & S	AGRI	TRADE	P&M	ELMT
AD&M	1.8%	1.3%	1.2%	1.0%	0.9%	0.3%	1.9%	1.2%	0.8%
PROF	2.8%	2.0%	1.9%	1.5%	1.3%	0.4%	2.9%	1.9%	1.2%
TECH	1.5%	1.1%	1.0%	0.8%	0.7%	0.2%	1.6%	1.0%	0.7%
Clerks	5.7%	4.1%	3.9%	3.1%	2.8%	0.9%	6.0%	3.9%	2.5%
S & S	2.2%	1.6%	1.5%	1.2%	1.1%	0.3%	2.3%	1.5%	1.0%
AGRI	0.3%	0.2%	0.2%	0.2%	0.2%	0.0%	0.3%	0.2%	0.1%
TRADE	0.5%	0.3%	0.3%	0.3%	0.2%	0.1%	0.5%	0.3%	0.2%
P&M	1.5%	1.1%	1.1%	0.8%	0.7%	0.2%	1.6%	1.0%	0.7%
ELMT	1.0%	0.7%	0.7%	0.5%	0.5%	0.2%	1.1%	0.7%	0.4%
2013									
AD&M	5.0%	4.1%	2.9%	1.1%	1.7%	0.3%	2.7%	1.7%	1.7%
PROF	6.7%	5.4%	3.9%	1.4%	2.3%	0.5%	3.6%	2.2%	2.3%
TECH	3.9%	3.2%	2.3%	0.8%	1.3%	0.3%	2.1%	1.3%	1.3%
Clerks	3.8%	3.1%	2.2%	0.8%	1.3%	0.3%	2.0%	1.3%	1.3%
S & S	2.4%	1.9%	1.4%	0.5%	0.8%	0.2%	1.3%	0.8%	0.8%
AGRI	0.2%	0.1%	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%
TRADE	0.2%	0.2%	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%
P&M	0.5%	0.4%	0.3%	0.1%	0.2%	0.0%	0.2%	0.2%	0.2%
ELMT	1.1%	0.9%	0.7%	0.2%	0.4%	0.1%	0.6%	0.4%	0.4%

Notes: Results are the proportion of male-female couples in each occupational pairing under randomised matching in Metropolitan area in 1986 and 2013. Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Appendix Table V: Assortative matching index of occupational pairings for 1986 and 2013 in all urban areas

	Occupational Index- All urban areas								
Female	**Male**								
	1986								
	AD&M	PROF	TECH	Clerks	S & S	AGRI	TRADE	P&M	ELMT
AD&M	0.37	-0.05	-0.03	-0.04	-0.03	-0.07	-0.08	-0.07	-0.06
	(0.2%)	(0.3%)	(0.3%)	(0.3%)	(0.3%)	(0.5%)	(0.5%)	(0.3%)	(0.4%)
PROF	-0.03	0.32	0.03	-0.02	-0.03	-0.08	-0.08	-0.10	-0.09
	(0.3%)	(0.2%)	(0.3%)	(0.4%)	(0.4%)	(0.7%)	(0.3%)	(0.4%)	(0.5%)
TECH	-0.03	0.05	0.10	0.00	-0.01	-0.04	-0.03	-0.05	-0.03
	(0.5%)	(0.4%)	(0.3%)	(0.3%)	(0.3%)	(0.5%)	(0.4%)	(0.4%)	(0.3%)
Clerks	0.00	-0.08	0.07	0.13	0.03	-0.19	0.06	-0.10	-0.08
	(0.4%)	(0.6%)	(0.5%)	(0.6%)	(0.6%)	(1.2%)	(0.4%)	(0.6%)	(0.8%)
S & S	-0.05	-0.08	-0.03	0.00	0.10	-0.03	0.03	0.05	0.05
	(0.3%)	(0.3%)	(0.3%)	(0.4%)	(0.3%)	(0.6%)	(0.3%)	(0.3%)	(0.4%)
AGRI	-0.15	-0.09	-0.08	-0.06	-0.05	0.53	-0.11	-0.02	-0.02
	(0.9%)	(0.7%)	(0.7%)	(0.6%)	(0.6%)	(0.2%)	(0.9%)	(0.7%)	(0.5%)
TRADE	-0.10	-0.09	-0.04	-0.01	-0.03	-0.01	0.21	0.06	0.03
	(0.9%)	(0.7%)	(0.6%)	(0.6%)	(0.5%)	(0.3%)	(0.7%)	(0.7%)	(0.5%)
P&M	-0.13	-0.11	-0.07	-0.01	-0.02	-0.02	0.06	0.20	0.08
	(0.5%)	(0.3%)	(0.3%)	(0.3%)	(0.3%)	(0.4%)	(0.4%)	(0.3%)	(0.3%)
ELMT	-0.13	-0.11	-0.07	-0.01	-0.02	0.00	0.03	0.15	0.14
	(0.6%)	(0.5%)	(0.4%)	(0.4%)	(0.4%)	(0.4%)	(0.5%)	(0.4%)	(0.3%)
	2013								
AD&M	0.16	-0.04	-0.02	-0.06	-0.03	-0.08	-0.03	-0.07	-0.05
	(0.2%)	(0.3%)	(0.3%)	(0.5%)	(0.4%)	(0.8%)	(0.3%)	(0.4%)	(0.4%)
PROF	-0.03	0.24	0.02	-0.03	-0.05	-0.08	-0.07	-0.14	-0.09
	(0.3%)	(0.2%)	(0.3%)	(0.6%)	(0.5%)	(0.9%)	(0.4%)	(0.5%)	(0.5%)
TECH	-0.02	-0.01	0.07	0.01	-0.01	-0.03	0.00	-0.01	-0.02
	(0.3%)	(0.2%)	(0.2%)	(0.4%)	(0.3%)	(0.6%)	(0.2%)	(0.3%)	(0.3%)
Clerks	-0.01	-0.05	0.00	0.08	-0.02	-0.03	0.04	0.03	0.01
	(0.3%)	(0.3%)	(0.3%)	(0.4%)	(0.3%)	(0.6%)	(0.2%)	(0.3%)	(0.3%)
S & S	-0.08	-0.11	-0.03	0.00	0.12	0.02	0.04	0.06	0.02
	(0.4%)	(0.3%)	(0.2%)	(0.4%)	(0.2%)	(0.5%)	(0.3%)	(0.2%)	(0.2%)
AGRI	-0.17	-0.13	-0.07	-0.03	-0.04	0.40	-0.05	0.03	-0.01
	(1.4%)	(1.2%)	(0.9%)	(0.5%)	(0.7%)	(0.2%)	(1.0%)	(0.6%)	(0.7%)
TRADE	-0.14	-0.11	-0.04	0.00	-0.02	0.00	0.26	0.01	0.02
	(1.6%)	(1.3%)	(1.0%)	(0.5%)	(0.7%)	(0.4%)	(0.7%)	(0.8%)	(0.8%)
P&M	-0.18	-0.15	-0.07	0.01	-0.02	0.00	0.06	0.26	0.06
	(0.9%)	(0.9%)	(0.6%)	(0.3%)	(0.5%)	(0.2%)	(0.6%)	(0.4%)	(0.4%)
ELMT	-0.11	-0.08	-0.05	0.00	-0.02	0.00	0.00	0.08	0.15
	(0.6%)	(0.5%)	(0.4%)	(0.2%)	(0.3%)	(0.3%)	(0.4%)	(0.3%)	(0.2%)

Notes: Results are the occupational assortative matching index for couples in all urban areas combined with same type of occupation in 1986 and 2013. Index is calculated as : $\frac{Actual-Random}{Max\ homogamy-Random}$. Standard errors in brackets (standard errors are the standard deviations from 250 replications of randomisation). Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Appendix Table W: Assortative matching index of occupational pairings for 1986 and 2013 in non-metropolitan areas

Index- Non-metropolitan areas									
Female	**Male**								
1986									
	AD&M	PROF	TECH	Clerks	S & S	AGRI	TRADE	P&M	ELMT
AD&M	0.41	-0.06	-0.03	-0.04	-0.03	-0.07	-0.09	-0.08	-0.06
	(0.4%)	(0.6%)	(0.6%)	(0.7%)	(0.7%)	(0.7%)	(0.8%)	(0.8%)	(0.8%)
PROF	-0.04	0.36	0.03	-0.02	-0.04	-0.08	-0.06	-0.09	-0.07
	(0.6%)	(0.5%)	(0.7%)	(0.9%)	(0.9%)	(1.0%)	(0.6%)	(0.6%)	(0.9%)
TECH	-0.06	0.05	0.10	0.01	-0.01	-0.03	-0.02	-0.05	-0.01
	(0.9%)	(0.7%)	(0.6%)	(0.6%)	(0.6%)	(0.6%)	(0.9%)	(0.9%)	(0.5%)
Clerks	-0.01	-0.06	0.07	0.10	0.04	-0.15	0.08	-0.06	-0.07
	(0.8%)	(1.1%)	(1.0%)	(1.1%)	(1.2%)	(1.4%)	(0.6%)	(0.8%)	(1.3%)
S & S	-0.07	-0.11	-0.03	0.01	0.11	-0.04	0.03	0.06	0.07
	(0.7%)	(0.8%)	(0.7%)	(0.9%)	(0.7%)	(0.9%)	(0.5%)	(0.6%)	(0.8%)
AGRI	-0.14	-0.08	-0.07	-0.05	-0.05	0.49	-0.11	-0.01	-0.02
	(1.2%)	(1.0%)	(0.9%)	(0.8%)	(0.8%)	(0.4%)	(1.4%)	(1.1%)	(0.7%)
TRADE	-0.09	-0.08	-0.02	-0.02	-0.03	-0.02	0.23	0.05	0.01
	(1.9%)	(1.5%)	(1.4%)	(1.2%)	(1.3%)	(1.1%)	(1.5%)	(1.7%)	(1.3%)
P&M	-0.12	-0.10	-0.06	-0.01	-0.01	-0.01	0.05	0.20	0.06
	(0.9%)	(0.7%)	(0.6%)	(0.6%)	(0.5%)	(0.6%)	(0.8%)	(0.6%)	(0.5%)
ELMT	-0.09	-0.09	-0.06	0.00	-0.03	0.00	0.00	0.16	0.12
	(1.1%)	(0.8%)	(0.8%)	(0.6%)	(0.7%)	(0.6%)	(1.2%)	(0.9%)	(0.5%)
2013									
AD&M	0.15	-0.05	-0.01	-0.05	-0.02	-0.07	-0.03	-0.06	-0.04
	(0.3%)	(0.6%)	(0.6%)	(1.2%)	(0.8%)	(1.0%)	(0.6%)	(0.6%)	(0.7%)
PROF	-0.04	0.27	0.03	-0.02	-0.01	-0.06	-0.03	-0.10	-0.07
	(0.6%)	(0.5%)	(0.7%)	(1.4%)	(0.8%)	(1.2%)	(0.6%)	(0.7%)	(0.8%)
TECH	-0.02	-0.01	0.05	0.01	-0.01	-0.02	0.01	-0.01	-0.01
	(0.6%)	(0.6%)	(0.5%)	(1.0%)	(0.7%)	(0.8%)	(0.5%)	(0.5%)	(0.6%)
Clerks	0.01	-0.04	0.01	0.07	-0.03	-0.04	0.03	0.01	-0.01
	(0.5%)	(0.6%)	(0.5%)	(0.9%)	(0.7%)	(0.8%)	(0.4%)	(0.5%)	(0.6%)
S & S	-0.06	-0.08	-0.03	0.01	0.11	0.00	0.02	0.05	0.02
	(0.6%)	(0.6%)	(0.5%)	(0.9%)	(0.5%)	(0.7%)	(0.5%)	(0.4%)	(0.6%)
AGRI	-0.14	-0.08	-0.07	-0.02	-0.04	0.41	-0.08	-0.01	-0.01
	(1.9%)	(1.3%)	(1.2%)	(0.6%)	(1.2%)	(0.5%)	(1.6%)	(1.3%)	(1.1%)
TRADE	-0.12	-0.07	-0.04	-0.01	-0.02	-0.01	0.26	0.00	0.03
	(2.7%)	(1.8%)	(1.8%)	(0.9%)	(1.7%)	(1.3%)	(1.6%)	(1.9%)	(1.5%)
P&M	-0.14	-0.10	-0.05	0.00	-0.05	0.01	-0.01	0.27	0.05
	(1.4%)	(1.1%)	(1.0%)	(0.6%)	(0.9%)	(0.6%)	(1.3%)	(0.8%)	(0.8%)
ELMT	-0.10	-0.06	-0.05	0.00	-0.03	0.01	-0.02	0.09	0.15
	(1.0%)	(0.8%)	(0.7%)	(0.5%)	(0.6%)	(0.5%)	(0.8%)	(0.7%)	(0.5%)

Notes: Results are the occupational assortative matching index for couples in Non-metropolitan areas with same type of occupation in 1986 and 2013. Index is calculated as : $\frac{Actual-Random}{Max\ homogamy-Random}$. Standard errors in brackets (standard errors are the standard deviations from 250 replications of randomisation). Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

Appendix Table X: Assortative matching index of occupational pairings for 1986 and 2013 in Metropolitan areas

	Index- Metropolitan areas								
Female	**Male**								
	1986								
	AD&M	PROF	TECH	Clerks	S & S	AGRI	TRADE	P&M	ELMT
AD&M	0.36	-0.04	-0.03	-0.04	-0.03	-0.07	-0.08	-0.07	-0.06
	(0.3%)	(0.4%)	(0.4%)	(0.4%)	(0.4%)	(0.8%)	(0.5%)	(0.4%)	(0.4%)
PROF	-0.03	0.31	0.03	-0.02	-0.03	-0.08	-0.08	-0.10	-0.10
	(0.4%)	(0.3%)	(0.4%)	(0.5%)	(0.5%)	(0.9%)	(0.4%)	(0.5%)	(0.6%)
TECH	-0.02	0.05	0.10	0.00	-0.01	-0.04	-0.03	-0.05	-0.04
	(0.5%)	(0.4%)	(0.3%)	(0.4%)	(0.3%)	(0.7%)	(0.5%)	(0.4%)	(0.4%)
Clerks	0.00	-0.09	0.07	0.13	0.03	-0.20	0.06	-0.11	-0.08
	(0.5%)	(0.7%)	(0.6%)	(0.6%)	(0.7%)	(1.8%)	(0.5%)	(0.7%)	(1.0%)
S & S	-0.05	-0.07	-0.02	0.00	0.10	-0.04	0.02	0.04	0.04
	(0.4%)	(0.4%)	(0.4%)	(0.4%)	(0.4%)	(0.8%)	(0.4%)	(0.3%)	(0.4%)
AGRI	-0.16	-0.10	-0.08	-0.07	-0.05	0.57	-0.11	-0.05	-0.03
	(1.4%)	(1.1%)	(1.0%)	(0.9%)	(0.8%)	(0.2%)	(1.4%)	(1.0%)	(0.7%)
TRADE	-0.10	-0.10	-0.04	-0.01	-0.03	-0.01	0.20	0.07	0.03
	(1.1%)	(0.8%)	(0.7%)	(0.6%)	(0.7%)	(0.3%)	(0.8%)	(0.6%)	(0.6%)
P&M	-0.14	-0.11	-0.07	-0.01	-0.02	-0.02	0.07	0.20	0.09
	(0.6%)	(0.4%)	(0.4%)	(0.4%)	(0.4%)	(0.7%)	(0.5%)	(0.3%)	(0.3%)
ELMT	-0.14	-0.11	-0.07	-0.01	-0.02	0.00	0.04	0.15	0.15
	(0.7%)	(0.5%)	(0.5%)	(0.5%)	(0.4%)	(0.5%)	(0.6%)	(0.4%)	(0.3%)
	2013								
AD&M	0.16	-0.04	-0.02	-0.06	-0.04	-0.07	-0.04	-0.08	-0.06
	(0.2%)	(0.3%)	(0.3%)	(0.6%)	(0.4%)	(1.1%)	(0.4%)	(0.5%)	(0.5%)
PROF	-0.03	0.23	0.01	-0.04	-0.07	-0.08	-0.08	-0.15	-0.09
	(0.3%)	(0.3%)	(0.4%)	(0.8%)	(0.5%)	(1.4%)	(0.4%)	(0.6%)	(0.6%)
TECH	-0.03	-0.02	0.07	0.00	-0.01	-0.03	0.00	-0.01	-0.02
	(0.3%)	(0.3%)	(0.3%)	(0.5%)	(0.4%)	(0.8%)	(0.3%)	(0.4%)	(0.4%)
Clerks	-0.02	-0.06	0.00	0.08	-0.01	-0.02	0.04	0.03	0.02
	(0.3%)	(0.3%)	(0.3%)	(0.4%)	(0.4%)	(0.8%)	(0.3%)	(0.4%)	(0.4%)
S & S	-0.08	-0.11	-0.03	0.00	0.13	0.01	0.04	0.05	0.02
	(0.5%)	(0.4%)	(0.3%)	(0.4%)	(0.2%)	(0.7%)	(0.3%)	(0.3%)	(0.3%)
AGRI	-0.17	-0.14	-0.05	-0.03	-0.05	0.39	-0.04	0.03	-0.02
	(2.1%)	(1.6%)	(1.4%)	(0.7%)	(1.0%)	(0.3%)	(1.2%)	(0.9%)	(1.0%)
TRADE	-0.14	-0.13	-0.05	0.00	-0.02	0.00	0.27	0.02	0.02
	(1.7%)	(1.6%)	(1.2%)	(0.7%)	(0.8%)	(0.4%)	(0.8%)	(0.9%)	(0.8%)
P&M	-0.19	-0.16	-0.08	0.01	-0.01	0.00	0.08	0.25	0.06
	(1.1%)	(1.0%)	(0.7%)	(0.4%)	(0.6%)	(0.3%)	(0.7%)	(0.4%)	(0.5%)
ELMT	-0.12	-0.09	-0.05	0.00	-0.01	-0.01	0.01	0.07	0.16
	(0.8%)	(0.6%)	(0.5%)	(0.3%)	(0.3%)	(0.4%)	(0.4%)	(0.3%)	(0.3%)

Notes: Results are the occupational assortative matching index for couples in Metropolitan areas with same type of occupation in 1986 and 2013. Index is calculated as : $\frac{Actual-Random}{Max\ homogamy-Random}$. Standard errors in brackets (standard errors are the standard deviations from 250 replications of randomisation). Abbreviations: AD&M – Legislators, Administrators and Managers; PROF – Professionals; TECH – Technicians and Associate Professionals; CLERKS – Clerks; S&S – Service and Sales Workers; AGRI - Agriculture and Fishery Workers;TRADE – Trades Workers; P&M – Plant and Machine Operators and Assemblers;ELMT – Elementary occupations (incl. Residual)

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