Online appendix of the paper entitled

A NEW METHOD FOR IDENTIFYING THE ROLE OF MARITAL PREFERENCES AT SHAPING MARRIAGE PATTERNS

ANNA NASZODI*   FRANCISCO MENDONCA

*Corresponding author: Anna Naszodi, European Commission's Joint Research Centre (Address: Via Fermi 2749, I-21027, Ispra, Italy) and Centre for Economic and Regional Studies (KRTK) (Address: TĂłth KĂĄlmĂĄn utca 4, H-1097, Budapest, Hungary). Emails: anna.naszodi@ec.europa.eu, anna.naszodi@gmail.com. Phone: +39-0332783948. Fax: +39-0332785733. Francisco Mendonca, European Commission's Joint Research Centre.

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APPENDIX A: SOME CONSIDERATIONS ON COMPARING MEASURES AND MEASURE SELECTION

In this appendix, we discuss some considerations we made in our paper (Naszodi and Mendonca 2021) in relation to comparing different measures of assortativity in marital preferences and choosing the criteria for measure selection.

First, we explain the added value of the new method to the problem of comparing the Liu–Lu matrix with other matrix-valued measures. In the literature, such comparison of measures are typically performed across aggregate scalar-valued measures and not across matrix-valued measures. An example for a scalar-valued aggregate measure is the Altham's index calculated from the matrix of odds ratios (see Altham 1970). Another example is the aggregate marital sorting parameter calculated from the diagonal elements of the marital sorting matrix. The latter was proposed by Eika, Mogstad, and Zafar (2019) as an alternative of the Altham's index.[1]

In our paper, we propose a novel approach for transforming matrix-valued measures to scalar-valued aggregates before their comparison: we propose to use counterfactual decomposition. In the empirical part of our paper, we apply this new approach before comparing three competing matrix-valued measures, i.e., the generalized Liu–Lu measure, the matrix of odds ratios, and the marital surplus matrix in Choo and Siow (2006). We construct counterfactuals in three different ways, i.e., by applying the new method (compatible with characterizing marital preferences by the Liu–Lu matrix), and two conventional methods (compatible with the odds ratios and the marital surplus matrix). The decomposed variable is the scalar-valued change in the share of homogamous couples. Thereby, the components are scalar-valued as well. Our focus is on the component capturing the contribution of marital preferences to

[1] According to Eika et al. (2019), it is difficult to give the Altham index a cardinal interpretation. This is not the case with the aggregate marital sorting parameter.

the observed change in the prevalence of homogamy. It represents a scalar-valued aggregate measure constructed from a matrix-valued measure.

Our favorite scalar-valued aggregate measure, i.e., *our index of changing marital preferences* is calculated from the Liu–Lu matrix. By construction, *our index takes into account all the elements of the matrix-valued measure*, the Liu–Lu matrix. *In addition, it has a natural interpretation: it quantifies how much has the share of homogamous couples changed in a given period due to changes in the marital preferences.*

Next, we present an important point relevant for choosing the criterion for method selection. *Our empirical criterion for method/measure/model selection is not the out-of-sample fit.* Instead of using one set of observations to train the models and another set of observations (independent from the training data) to compare the prediction errors, we do the following. First, we use census data and each of the competing methods to characterize marital preferences of the generations under study. Then we compare the model implied generation-specific preferences with an alternative source of data (covering a subset of individuals in the census data) on the same phenomenon. In particular, we use survey data characterizing the preferences of the same generations.

The significance of our point is this: certain commonly applied out-of-sample fit tests (e.g. the Diebold–Mariano test) may mistakenly favor some simple models against other models with more parameters. Since our criterion is not the relative out-of-sample performance of the compared three models, we do not treat unfairly the most complex model, the Choo and Siow (2006) model.

APPENDIX B: DATA

Data used in Naszodi and Mendonca (2021) were extracted from the Integrated Public-Use Microdata (IPUMS henceforth) from the Minnesota Population Center.[2] These data are representative of the studied population by construction.

For the main analysis, we selected the sample as follows. First, we restricted the sample to those individuals whose "`age`" variable has a value higher or equal to 30 and less than 35 years.

Second, we used the "`edattain`" variable of males in our restricted sample and the "`edattain_sp`" variable of their partners. These education variables identify the highest level of education with four categories, i.e., "less than primary completed", "primary completed", "secondary completed", and "university completed". We used these variables to classify the males with a non-empty "`edattain_sp`" variable into 16 disjunct categories.

Third, we summed their personal weight ("`perwt`" variable) in each of the 16 categories.

Fourth, we calculated the educational distribution of single males and single females. Single people were defined as those whose marital status ("`marst`" variable) is not "married/in union". We summed their personal weight in the sample in each of the four educational categories and for both genders.

Finally, we merged the lowest two educational categories for the main analysis.

For one of the robustness checks, we skipped the last step of merging. For another robustness check, we repeated all the steps (including the merging) but used the "`edattain`" variable of females (instead of the "`edattain`" variable of males).

For the third robustness check, we used the detailed "`edattaind`" and "`edattaind_sp`" variables as well. Here, we split the category "`edattain`=secondary completed" into two sub-

[2]The data were downloaded from `https://doi.org/10.18128/D020.V7.1` on the 27th of March, 2018. The contingency tables we used can be downloaded from `http://dx.doi.org/10.17632/x2ry7bcm95.1` together with the new method implemented in Excel, Visual Basic, and R.

categories. One sub-category is where "`edattaind`" is either "some college" or "post secondary technical". For the sake of simplicity, we refer to this sub-category as "some college". While the other sub-category is its complementer in "`edattain`=secondary completed". We split the category "`edattain_sp`=secondary completed" similarly using "`edattaind_sp`".

APPENDIX C: POTENTIAL LIMITATIONS OF THE SUPPLEMENTARY ANALYSIS

In this appendix, we discuss some potential limitations of our supplementary analysis. First, the expressed views of the survey respondents might not represent well the views of married/in union Americans. This is because our sample of the survey respondents is relatively small consisting of only 526 individuals. In addition, its composition may be different from that of the studied population along certain dimensions relevant for mating preferences.

However, even if the share of survey respondents with a given view is systematically underrepresented in each generations, its difference across generations can be an unbiased estimate on its population counterpart. Moreover, some differences among the generation-specific views are statistically significant despite of having a small sample (see the confidence intervals in Fig. 3 of our paper). These points make us think that the survey data signal well at least the sign and the magnitude of differences in marital preferences across the generations under study.

Second, the variations of marital preferences detected in the survey data might reflect not only the intrinsic differences across generations that we are after, but these can also be influenced by the age of the respondents. The survey was conducted in one given year when the respondents from different generations belonged to different age groups.[3] If people

[3]For instance, in 2010 the early baby boomers were between 60 and 64 years old, the late boomers aged between 50 and 54 years, those who belong to the early generation-X aged between 40 and 44

appreciate a well-educated partner differently over the course of their lives, or, alternatively, if older survey respondents are more likely to express their views on the importance of certain qualities of their prospective daughters-in-law and sons-in-law rather than reporting about the qualities of their own preferred partners, then the age-effect might not be negligible.

Cleaning the measured variation of preferences across generations from the age-effect is possible only with data from more than one survey wave. Actually, the pair of questions used in this supplementary analysis appears not only in the Changing American Family survey, but also in another survey conducted by the Pew Research Center in 2017, The American Trends Panel Wave 28 survey. Therefore, researchers of the Pew Research Center could, in principle, separate the studied generation-effect from the age-effect. However, the publicly available data from the latter survey does not allow other researchers outside the Center to do so since it does not indicate the age of the respondents.[4]

Despite this problem, our survey data can still validate the new method under the following assumption: becoming 10 years older changes ones' views about the importance of spousal education to a given direction in every age group from the 30s up to 60s. For instance, if aging makes individuals less and less picky with respect to the education level of their mates then this tendency could potentially explain why the declared preferences for well-educated partners are weaker in the early generation-X then in the late generation-X. However, it cannot explain the detected difference between the self-reported preferences of the early boomers and the late boomers. The explanation of the latter is left for the generation-effect; its sign is the same as suggested by the new method.

Alternatively, if spousal education tends to matter more and more with age then the age-effect could explain in principle the difference between the early boomers and the late boomers, but not the significant difference between the early generation-X and the late

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years and the members of the late generation-X were between 30 and 34 years old.

[4]The public version of the data from the American Trends Panel Wave 28 survey can be downloaded from `https://www.pewsocialtrends.org/dataset/american-trends-panel-wave-28/`.

generation-X. Again, the explanation of the latter remains for the generation-effect whose magnitude is more in line with the results obtained with the new method.

All in all, at least one of the findings with the survey data convinces us about the good empirical performance of the new method if the strength of marital preferences over having a well-educated partner is monotonous in age. Otherwise, further analyses are needed.

REFERENCES

Altham, Patricia (1970) The measurement of association of rows and columns for an r×s contingency table. *Journal of the Royal Statistical Society Series B* 32 (1), 63–73.

Choo, Eugene and Aloysius Siow (2006) Who marries whom and why. *Journal of Political Economy* 114(1), 175–201.

Eika, Lasse and Magne Mogstad with Basit Zafar (2019) Educational assortative mating and household income inequality. *Journal of Political Economy* 127(6), 2795–2835.

Naszodi, Anna and Francisco Mendonca (2021) A new method for identifying the role of marital preferences at shaping marriage patterns. *Journal of Demographic Economics* XX(x), xxx-xxx.