BRJ Response paper 2: Immigration prediction tool

* Can we in some sense quantify the uncertainty that these prediction in terms of expected earnings behave? This might make it more
* Add something about the points we talked about in class (the three conditions when predictions are valid for policy/decision making)
* Are there reasons in the history why people have not moved to certain areas (not captured by the administrative data). Could there be biases in the data for example. Are there things that you do not want to select on?
* I think it could have been nice to do some data visualization of the immigration patterns. Or do a case study: This is person X which characteristics Y. How would the model do? Some visualizations are provided rather late in the paper now.
* Is there discussion about the potential biases in the system plus the discretion of the government. Some areas might react by making it more difficult for migrants to move (or the opposite)?
* This algorithm could increase segregation: sending some immigrants with a certain background to some locations. Do you get diversity (which is one of the goals). Moreover, maybe by relying on historical patterns, you reduce the effects instead of improving them.
* What about selection bias? Maybe people that move somewhere successful are more successful in general! (check appendix!)
* Counterfactual analysis would be needed: how would individual j have done if it would have gone to another area instead of area k? Hence do we use the correct type of model? Moreover, if before there was a selection bias of people moving to certain places: do we have the general correct assumption of iid data for the prediction?
* Nice schematic representation of the decision process
* When doing the RCT, it should be taken into account theat the final scheme will be voluntary. Hence can you extrapolate the results of that to the final effects of the recommender? Or do you design it such that it is randomized which people get the option to use it?
* The focus of the express program is on high skilled labour. What does this mean for the external validity of this recommender system? Are high-skilled labourers not very different from other types of immigrants? Moreover, the pool of migrants is already highly selective
* The system is only introduced in 2015. Hence do we already have enough “long-run” data?
* Moreover the historical data that is used will be potentially very different since it originates from before the express system.
* Maybe matching on scores could be done? Inverse probability weighting (which is related to matching) basically takes into account these covariate shifts between treatment and control groups.
* It could be interesting to also include different measures of success? Will earnings be the only thing that they care about?
* Is income over time corrected for?
* See the data leakage comment on page 8
* In the simulation, the predictions can also be looked at in the area where they actually moved. I would also look at uncertainty. Point predictions do not make sense at all imo…
* Model validation: when does the model perform well, when does it not? (some of them are randomly dropped in some simulations, making it more robust to the effects coming from a specific set of ERs). Can we stratify the errors that it makes (maybe it predicts super poorly but high for a certain region). Not only the R^2 is important! Also model explanation could have been added.
* The simulations are quite high on assumptions. Make it harder to interpret the results in context of policy gains.
* CAN WE STILL LINK IT TO THE 3 FACTORS DISCUSSED IN CLASS?
* The histograms on page 12 are not very interpretable…

Ferwerda et al: Leveraging the Power of Place: A Data-Driven Decision Helper to Improve the Location Decisions of Economic Immigrants

This paper researches whether implementing an algorithm that helps immigrants to choose their initial settling improves expected income of those immigrants. Specifically, the paper focuses on immigrants in the Canadian Express Entry system.

What is novel about this approach, is that no data driven approaches have been proposed in order to help immigrants settle in their new country. Immigrants often rely on heuristics and settle in places that they either know (from being the only place they know, or because they know people that moved there). In this way, the authors nicely embed their problem in the literature, by referring to the availability bias originating from behavioural economics and psychology. More generally, I appreciate how the authors position themselves in the literature and convey the social implications of their research.

The authors generate recommended locations for immigrants to move to by creating models that predict expected earnings of immigrants for each economic zone they can move to. These models take individual characteristics of the immigrants and of locations into account to predict these values. Historical data of both Express Entry and Non-Express Entry immigrants is used to train the models.

In general, the validation of the models for each location could be presented in a clearer way. The strength of the recommendation system is now mainly derived from the simulation study. For the individual fitted models, the (aggregated) R2 metric is given in a footnote. Also in the appendix there is not much information, except on optimal hyperparameters. What would give more insight though, is to visualise the R2 metric across locations. The authors repeatedly mention that current immigration patterns tend to be concentrated in only a few locations. That means that there will be much more data for those locations, potentially making the predictions of expected income better. This information could be perfectly displayed together with the variable importance measures for each location, which gives more policy relevance to the model (policy makers also get insight in what drives predictions).

Building on this idea of varying model quality, a second improvement could make the insights in the model better and might even improve recommendation adherence. Immigrants currently get a list of locations with highest predicted expected earnings. However, there are no uncertainty quantifications added to these predictions. In the literature, more attention is given to probabilistic forecasts, that in addition (or instead of) a point estimate also provide confidence bounds. Referring to the previous argument, regions that have historically known less immigration might also have worse prediction performance and hence the predictions can be trusted less. When confidence bounds are also presented to immigrants, this might also give more context than a mere point estimate of their expected earnings. Even for boosting models that do not give prediction intervals generally, this can easily be implemented with Conformal Prediction, a distribution free method that wraps around any black-box ML algorithm (Lei et al., 2018; Shafer & Vovk, 2008).

Lastly, in assessing the impact of the recommendations on society, the authors assume that a percentage of people will comply with the recommendation, and for those people, the extra earnings are quantified. However, in the introduction and discussion of the other literature, it is argued that a more uniform distribution of migrants might improve integration and foster growth. In this spirit, it would be interesting to add a component to the analysis that randomly recommends a location to immigrants (hence nudging immigrants to spread evenly over the country). The effect of such a recommendation system can then be quantified in a similar way. The interesting interpretation would then be to see how much the data-driven recommendation system is better than a random recommendation system. This does then not only describe what the added benefit of a recommendation system is over not having one, but also what the authors’ model adds on top of a recommender system in general.

The paper nicely discusses limitations as well as potential risks of implementing this recommender system in practice. I very much like how they disentangle the difference between the final goal of successful immigration and the short term metrics that the recommendation system focuses on. I would maybe add one more potential risk, being the endogeneity of the recommender system. When the system would mainly recommend similar locations to similar people, this might introduce segregation among immigrants, which could be considered as a negative effect.

Overall, the authors write a strong paper and show well how a data driven recommendation system to aid settling decisions could benefit economic growth. The paper does not only consider the technical details of developing such a model, but also gives a good sense of limitations and risks involved with such a system.

References

Lei, J., G’Sell, M., Rinaldo, A., Tibshirani, R. J., & Wasserman, L. (2018). Distribution-free predictive inference for regression. *Journal of the American Statistical Association*, *113*(523), 1094-1111.

Shafer, G., & Vovk, V. (2008). A Tutorial on Conformal Prediction. *Journal of Machine Learning Research*, *9*(3).