where

narios ~~that identify~~ choices used to estimate behaviour traits, train a prediction model on individuals in the data for whom that scenario is observed, and use that model to predict the trait for all individuals in the data – could, in principle, be used for other behaviour traits, too. Large-scale observational data of the type used in this study has become available only in recent years and is increasingly used across the social sciences. On~~c~~e challenge with such data is that they do not usually provide the same detailed information about behaviour traits that can be gained from observing a small set of people in a lab. Our approach has the potential to bridge that divide by allowing researchers to augment large-scale observational data with behaviour traits elicited from the data itself.

We find, however, that propensities for patience based on different choice scenarios are uncorrelated, suggesting that in our particular application, our approach is unsuccessful at eliciting underlying preferences. There are three ways in which our work could be refined in future research. First, identifying choice scenarios is made more challenging because of imperfect tagging of transactions in the data, and because we do not have direct access to the algorithms used for tagging. Using the approach on data with more complete and reliable tagging or in collaboration with the data provider, so that anomalies in the data can be identified and handled, could eliminate that source of risk. Second, the prediction models we used could be enhanced both with additional features and by the use of more sophisticated models and further tuning. In terms of features, we have already discussed that, in our context, adding variables that more fully capture users' financial constraints might have been useful. Furthermore, we have relied on a relatively straightforward set of features, that could probably be augmented. In terms of models, we have used a number of relatively simple "off-the-shelf" models. Using more advanced models could help provide more accurate predictions. Finally, it is possible that people the way people actually make intertemporal choices is not well captured, even approximately, by the discounting models on which our elicitation approach builds. If this is true, then either eliciting time-preferences based on a different framework, or focusing on eliciting different behaviour traits might prove more successful.

Chapter 3, also join work with Neil Stewart, calculates simple summary statistics of individuals' spending profiles and tests whether differences in spending profiles are predictive of the frequency with which individuals make transactions into their savings accounts. To summarise spending profiles, we calculate the entropy of an individual's spending profile in a given period, which captures the predictability of spending transactions in said period.

We focus on spending profiles for three reasons: first, our understanding of how individuals spend their money is largely based on survey data from a relamargin – users reduce the number of transactions they make rather than the value of the average transaction. Interestingly, users do not seem to use these additional funds to build up emergency savings: net-inflows into savings accounts do not change after signup. I can also neither find significant increases in flows into investment and pension accounts or additional savings accounts that are not linked to the app, not additional loan repayments. So where does the money go?

The main limitation of my approach is that I cannot isolate the effect of MDB use from possible confounding factors that let users to self-select into using the app in the first place, and that I cannot isolate the effect of individual components of the app such as information and goal-setting. However, I do find that app use is associated by a statistically and economically significantly reducuction of discretionary spend that is sustained for at least six months, and that seems to be brought about by a reduction in the number of purchases across a number of spending categories. This provides novel insights into how people who probably do have some unobserved motivation to reduce their savings actually achieve this. The additional finding that a reduction in spend is not accompanied by a commensurate increase in either short-term savings, investments, or debt-reduction suggests that people use the saved funds for a variety of different purposes. → And we don't have sufficient power to detect these smaller effects?

The findings also suggest promising directions for further research. First, the substantial drop in discretionary spend associated with app use does suggest that MDB and apps like it might have a positive causal impact on financial outcomes, making it worthwhile to study their effect in more detail in ways that account for the two limitations mentioned above. Second, the finding that people may direct saved funds towards a number of different purposes can be the result of differences in funds use across or within people or a combination of the two. Within people variation in fund use could suggest the possibility that people direct additional cash-flows towards a number of different uses instead of towards those with the highest payoff, such as paying down credit-card debt or investing in government-subsidised high-interest investments. Further research establishing to what extent there is within-person variation of fund use, and whether such funds are directed towards the most effective uses would provide further useful insights into savings behaviour, and could serve as the basis for further development of financial aggregator apps to help users direct saved funds towards the most effective users.