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Volatility prediction via interpretable models through the lens of vulnerability: An application to Open Banking

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ABSTRACT

This paper explores and predicts an account-level volatility based on personal Open Banking transactions, where volatile cash flows imply uncertainty in individuals' income and expenditure. A novel volatility index is proposed to combine inflows, outflows, and balances of an individual's account, that can be used to monitor the stability and risk of personal transactional behaviour. Further, we compare stateof-the-art statistical models and machine learning algorithms (SPLINE regression, tree-based ensembles, deep-learning models) to predict volatility into the future, and examine their predictive performance and interpretability. Our results show a strong connection between volatility and financial vulnerability, suggesting it is important to include past vulnerability-related transactional behaviour into volatility forecasts and general risk management. This study investigates specific dimensions of vulnerability that may drive cash flow volatility, and in addition, constructs a personal vulnerability index, which can be used separately for monitoring the signs of financial distress or as a predictor in the volatility models. Non-linear patterns provide insights into varying levels of harmful volatile behaviour. From the connection between volatility and vulnerability we identify target risk groups, in order to help financial firms in setting up effective strategies for financial planning and consumer protection.

KEYWORDS
volatility forecast; personal account; vulnerability; Open banking; risk management

1. Introduction

The EU Second Payment Services Directive (PSD2), also known as Open Banking (OB) in the UK, has been a game changer in the financial services sector. The Directive has enabled data sharing to regulated third-party financial service providers (TPP) based on consumers' consent. This initiative

provided a unique opportunity to obtain nuanced insights into consumers' financial behaviour based on their account transactions which have improved financial decisions, helped individuals to practise better money management and expanded access to financial services[1]. The Directive has also brought new challenges stemming from this new source of voluminous and unstructured data. One of such challenges is the need of new metrics, summarising various aspects of financial behaviour, that can be used in financial risk management. Finance literature on securities market views volatility as an important measure of risk and uncertainty. Volatility forecast has been a common financial model to evaluate uncertainty from the fluctuations in historical daily market closing prices of financial instruments to mitigate investment losses (Apergis, Barun´ık, & Lau, 2017; Barunik, Krehlik, & Vacha, 2016; Escobar-Anel, Rastegari, & Stentoft, 2021; Xiao & Aydemir, 2007). However, in the context of personal bank account transactions the concept of volatility is much less developed, and our paper addresses this gap. Measuring and modelling volatility is important since it directly affects the ability of financial institutions to make accurate predictions of customers' behaviour, thus impacting the quality of the financial planning and decisions.

Yet there is an additional concept of vulnerability that our paper explores and its connection to volatility. Previous studies showed that volatility of personal finance can arise because of poor financial health and wellbeing. Volatility can be connected with poor budget planning, failures to make ends meet and difficulties in allocating money for savings (Farrell & Greig, 2015, 2016). In situations of insufficient financial buffer, when unstable income fails to cover irregular spending, this mismatch between income and expenditure volatility is associated with deteriorating financial wellbeing (Gladstone, Nieboer, & Raghavan, 2020). Therefore, volatility is seen by many scholars as being driven by implicit risks leading to distress.

However, in contrast to securities, where market instability risk increases with stock price volatility, high personal volatility does not necessarily indicate high distress risk because volatilities could be driven by low-risk scenarios such as income bonus or seasonal holiday spending (Farrell & Greig, 2015, 2016). Whilst high volatility complicates forecasting in general, it becomes a particular concern when it is driven by vulnerability-related transactional behaviour. Therefore, volatility forecast has to be examined along with the underlying financial circumstances for an effective risk evaluation.

Volatility under vulnerable circumstances should raise concerns because vulnerability is a precarious state of being more susceptible to distress. In the household context, high vulnerability and high level of household debt are the precursors of financial crisis (Noerhidajati, Purwoko, Werdaningtyas, Kamil, & Dartanto, 2021; Subov´a, Mura, & Buleca, 2021). Vulnerable consumers are more prone to distressˇ because they are more likely to be excluded from financial services, and eventually suffer from low financial health as compared to an average consumer (Financial Conduct Authority, 2015). Thus, investigating the intertwined effect of volatility and vulnerability and assessing whether the cash flow uncertainty is related to a vulnerability-driven financial instability is essential for effective risk management.

This study develops a personal account-level volatility model to forecast future volatility from past transactional behaviour. The earlier investigation has proposed a personal account volatility index which combines fluctuations in inflow, outflow, and balance, to evaluate the degree of uncertainty in OB cash flow transactions (Goh, Andreeva, & Cao, 2022). That preliminary study has focused on exploring the relationship between transactional patterns and volatility, without developing future predictions. Similarly, other previous personal volatility studies have mainly focused on concurrent exploration of the economic drivers of volatility (Andersen, Austin, Doucette, Drazkowski, & Wood, 2015; Farrell & Greig, 2015, 2016) or its connection with financial health (Gladstone et al., 2020), but not for the purpose of assessing future risks. Estimating risks projected from past behaviour are key to

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[1]https://openbanking.foleon.com/live-publications/the-open-banking-impact-report-june-2022/

mitigate risk and minimise losses (Apergis et al., 2017; Thomas, Crook, & Edelman, 2017; Xiao & Aydemir, 2007), and yet no such risk model has been developed in the personal finance literature. To address this gap, we extend our preliminary work to build a personal account volatility prediction model. Specifically, we use the defined volatility index as the target variable and we include as predictors not only the past volatilities, but also past transactional behaviour that relate to various vulnerable conditions. To the best of our knowledge, this has not been done before.

Given a scarce literature on relationship between volatility and vulnerability, we formulate a wide range of covariates quantifying vulnerability-related transactional behaviour, in order to gain insights which behavioural aspects are most important predictors of volatility. In addition, we construct a personal vulnerability index to summarise the vulnerable characteristics in a single measure. Such index is useful on its own to rank customers according to the level of financial risk. It is also included as an additional predictor. There is no universally accepted vulnerability measure in the literature. A limited number of papers propose household vulnerability index from various aspects of distress conditions (Nicol´as & Peter, 2013; Noerhidajati et al., 2021; Subov´a et al., 2021; Yijia & Grace, 2007), but they are based on surveys,ˇ i.e. self-reported data that may be subjected to various biases and inaccuracies. The advantage and novelty of our study consists in proposing the account-level index based on objective financial transactions. Financial Conduct Authority (2021) provides some guidance on the key characteristics of vulnerable consumers, however they do not suggest how these characteristics could be combined. Taking advantage of the transactional data, this study defines a novel account-level vulnerability index in the OB context based on the drivers outlined in Financial Conduct Authority (2021).

Since OB is a relatively new field, we compare most popular statistical and state-of-the-art ML models in terms of predictive accuracy and explainability. Model interpretability is the main consideration in developing an account volatility prediction model from risk assessment point of view because of the regulatory requirement to deploy transparent consumer risk assessment (Grennepois & Robin, 2019). Another desirable property is the model's ability to capture any complex non-linear patterns that may exist, since the relationship between volatility and vulnerability is not straightforward. From previous research on similar personal finance applications, spline regression is a potential candidate model, given its flexibility in modelling irregular shapes in dynamic behaviour over time (Djeundje & Crook, 2019a, 2019b; Luo, Kong, & Nie, 2016) and predicting credit defaults (Giordani, Jacobson, Von Schedvin, & Villani, 2014).

Tree ensembles and deep learning ML techniques are also well-known for their capability to handle various data structures such as complex credit consumers' behaviour (Gunnarsson, Vanden Broucke, Baesens, Oskarsd´ottir, & Lemahieu, 2021;´ Lessmann, Baesens, Seow, & Thomas, 2015), text data (Kriebel & Stitz, 2021), directional movement of stocks (Fischer & Krauss, 2018), or traders' risk-taking behaviour (Krauss, Do, & Huck, 2017). Post-hoc interpretations of black-box ML models have gained attention in financial applications e.g. Shapley values reveal the importance of default predictors in peer-to-peer lending (Bussmann, Giudici, Marinelli, & Papenbrock, 2021) or mortgages (Bracke, Datta, Jung, & Sen, 2019), and accumulated local effect plots describe the non-monotonicity in the features driving credit loss given default (Bastos & Matos, 2022). The successful applications of ML in financial risk modelling, coupled with a post-hoc explainability, could be a potential alternative to develop an account-level volatility prediction model. We compare the predictive performance of several candidate models, as well as the interpretations of statistical models' marginal effects with the outputs from accumulated local effect plots. Hence, this comprehensive benchmark experiment provides a baseline reference for the future development of personal financial risk models.

This study contributes to the personal finance and risk modelling literature in the following ways. First, we examine the way to forecast the future volatility of existing or new personal accounts, based on previous transactional patterns. We quantify a wide range of vulnerability indicators and combine them into a single measure. This provides an innovative analytical support to account risk management

in the area of OB. Second, we benchmark several algorithms and show that spline regression is competitive with ML models in account volatility predictions because it captures non-linearities while preserving the intrinsic interpretability. The interpretations of non-linear transactional patterns provide insights into varying levels of harmful volatile behaviour. Third, we identify target risk groups from the connection between volatility and vulnerability to help financial firms in setting up effective strategies for financial planning and consumer protection.

The paper has the following structure. The next section 2 outlines the methodology with data description, definitions of the target variable, and covariates, the models included in the benchmark experiment, and the model explainability approaches. Section 3 reports and discusses the results. We analyse the components in financial volatility, compare the predictive performance, interpret the non-monotonic patterns from spline regression's marginal effects to highlight varying degrees of risky volatile behaviour and identify target risk groups, as well as compare the explanability between spline regression and the best performing machine learning model. Finally, section 4 concludes.

2. Methodology

2.1. Data description

Over 9 million rows of transactions from 11,150 UK personal bank accounts are used in this study. Each account contains 12 months of transactional history. Each transaction has a date, a short description, a credit or debit indicator, an amount, a label for the income or expenditure category, and the account balance after the transaction. Table 1 describes the raw transactional records.

[Table 1 about here.]

Since the aim of this study is to predict the future volatility of existing or new accounts from their past transactional patterns, we follow a standard set up adopted in consumer credit risk assessment, aka credit scoring (details in (Thomas et al., 2017)). Traditionally, application credit scoring is used to assess the risk of new borrowers, whilst the behavioural credit scoring is applied to existing customers, in order to decide on potential actions, e.g. changing the credit limit. Credit scoring in its standard form relies on cross-sectional models, where changes in behaviour are summarised by specific variables that capture certain patterns within a particular time period, e.g. number of delinquencies in the past three months.

The data set is split into a training set, an out-of-time in-sample test set (existing account) and an out-of-time out-of-sample test set (new accounts), as illustrated in Figure 1. The training set consists of 70% randomly chosen accounts, with transactional data from the first and second quarters and volatility data from the third. Therefore, the models are trained to forecast the personal account's volatility one quarter ahead, using predictors/covariates from the past two quarters. The out-of-time in-sample test set applies the trained models to the same 70% randomly selected accounts to predict the volatility in Q4 from transactions in Q2 and Q3, while the out-of-time out-of-sample test set applies the trained models to the remaining 30% accounts.

[Figure 1 about here.]

2.2. Definition of financial volatility

We propose an index that combines different aspects of volatility that refer to an account's financial buffer, income and expenditure (Goh et al., 2022). The financial buffer is defined as the available balance amount. A single measure of financial volatility allows to rank-order the customers according

to the degree of the uncertainty they represent for modelling. The volatility index is computed from three months of transactions, Q3 in the training set and Q4 in the test sets.

To construct the volatility index, we use three variables: daily balance, monthly inflow, and monthly outflow. Each account's daily balance is a time series of end-ofday balance that spans over three months with a few exceptions, where accounts have transactions ending in the middle of the month. We obtain a monthly series of inflow and outflow by aggregating the daily credit (positive or incoming) and debit (negative or outgoing) amounts. The coefficient of variation (CV), which is a popular measure of volatility in Finance, is used to calculate the volatility of each account. It quantifies the standard deviation of each data series relative to the corresponding mean, and is useful when comparing the variation of different time series, even when the means are very different. We use these CVs as inputs into Principal Component Analysis (PCA) (in Appendix 3) to calculate the optimal weights for three dimensions of data to construct the volatility index.

2.3. Covariate creation

The covariates are constructed from four main aspects characterising the financial behaviour: balance, inflow, outflow, and spending on specific categories. In addition to general summary measures describing the individuals' prevailing financial conditions, we look for downward trends that might signal deteriorating financial circumstances. We consider a short-term trend, that is, whether the current month has a lower value relative to the previous month, and a longer term one over the six months by examining three month rolling windows (six months of transactional records give four three-month rolling windows).

The balance is used to extract the patterns on a daily and monthly bases, which then form the following groups of covariates, as shown in Appendix A. The daily balance measures (X1-X5) track the fluctuations during a day, whereas the monthly balance covariates (X6-X8) evaluate the financial position at month end. Potential distress refers to the following four overdraft use scenarios (X9-X12): when an account has (i) gone into the overdraft at least once in a month, (ii) a negative month end balance, (iii) a larger negative month end balance than a negative month open balance, and (iv) a negative month end balance where more than half of the month is in a negative balance. The latter two scenarios outline severe overdraft usage. In addition, we examine the dynamics of the lowest monthly balance (X13-X16) that corresponds to the worst-case scenario, the declining trend indicates the deterioration of the worst financial position.

Income and expenditure behaviour are summarised from the incoming and outgoing transactions, with the focus on amount, frequency, and the number of days, when certain transactions occur (X17-X34). To characterise spending behaviour in specific categories (X35-X92), we focus on payment patterns in fixed costs, living costs and debts. Additionally, we also exploit expenses information that may infer unhealthy financial conditions. For instance, regular gambling may imply addictive behaviour whilst occasional healthcare and medical expenses may signal unexpected life events.

We also include the composite measure of vulnerability (X93) which captures its four key drivers, as defined by the regulator (Financial Conduct Authority, 2021): (1) poor health, which affects normal daily life; (2) experiencing unexpected life events such as unemployment or bereavement; (3) having low resiliency to financial or emotional shocks, and (4) having low capability and insufficient knowledge in money management. We cannot directly observe these drivers, however, we can identify transactions or patterns that are logically related to the above listed drivers. Therefore, we define a vulnerability index from a list of the following numeric attributes: the total healthcare expenditure, the total income loss (total decreased inflow amount relative to the previous month), the total amount of benefits received, the debt amount (sum of loan and overdraft amounts), the debt-to-inflow ratio, the outflow-to-inflow ratio, the buffer-to-outflow ratio (buffer is the sum of available balance and savings)

and the expenses on social activities or hobbies. We employ PCA (in Appendix B) to assign weights and aggregate the attributes to construct the composite vulnerability index.

Table 2 summarises the list of covariates in each aspect and outlines three types of model setup. If the objective is prediction only, then a basic model specification to predict a target variable of interest would utilise the same variable from the past. Therefore, Type 1 inspects how past volatility directly influences the future one. However, it is reasonable to assume that future volatility also depends on financial circumstances, and financial difficulties, in particular. So, Type 2 examines the impact of vulnerability on future volatility, and Type 3 investigates whether vulnerability risk provides additional predictive power on top of the past volatility. The full list of covariates with more detailed description can be found in Appendix A. In addition to the vulnerability index, there are a total of 93 covariates.

[Table 2 about here.]

2.4. Predictive models and explainability

We compare the performance of standard statistical models and several state-ofthe-art ML techniques from the tree ensemble and neural network families. Linear regression (LIN) is included as the simplest widely used algorithm, as a benchmark to compare more advanced techniques. The selection of other statistical techniques is guided by the presence of non-linear patterns, where quantile (LIN-Q) and spline regressions (SPLINE) would be appropriate. The selection of advanced ML algorithms i.e., random forest (RF), extreme gradient bossting regressor (XGB), multilayer perceptron network (MLP) and deep belief network (DBN) is prompted by the studies of the predictive performance in credit scoring (Ala'raj, Abbod, Majdalawieh, & Jum'a, 2022; Gunnarsson et al., 2021; Kriebel & Stitz, 2021; Lessmann et al., 2015; West, 2000), where these algorithms have shown superior predictive accuracy. Quantile gradient boosting regressor (GBR-Q) is also included as the counterpart comparison of LIN-Q. The descriptions of each model can be found in Appendix C.

To reveal the underlying non-linear relationships between the covariates and financial volatility, we examine the marginal effects from SPLINE and also accumulated local effects (ALE) plots, detailed in Appendix D.

3. Results and discussions

3.1. Volatility index

Table 3 reports the eigenvector, eigenvalues, and percentage of explained variance for each PC estimated from the three dimensions of financial behaviour. We construct the volatility index using the first two principal components as they explain 88% of the information variance and discard the third component as we consider 12% of the explained variance as unusual noise in the data.

[Table 3 about here.]

The eigenvectors represent the contribution of each financial behaviour within the latent structures. As shown in Table 3, the high weights of first PC for inflow and outflow suggest that these are the more important components of the volatility index. The contribution of balance fluctuation is further captured in PC2, to provide additional information on overall volatility. From the evenly-distributed weights reported in the last column of Table 3, all three dimensions are equally important to measure individuals' overall volatility.

3.2. Predictive performance

Table 4 reports the root mean squared error (RMSE) and mean absolute error (MAE) for in-sample and out-of-sample test sets to evaluate the predictive performance of the models across the three types of model setup.

[Table 4 about here.]

We use Type 1 as the baseline scenario where only the past values are used to predict the future. Most models in Type 2 report a slightly higher error than Type 1. Thus, the volatility covariates have stronger predictive power than the vulnerability covariates. On the other hand, most models in Type 3 have a better performance than Type 1, indicating vulnerability adds predictive power on top of the volatility covariates.

All models are highly competitive with each other. There is only a marginal 1-8% difference between the best (in **bold**) and worst (in *italic*) model performance. Across the three model types, the tree ensemble techniques, RF have the best performance with the lowest errors in most cases. The quantile regression models, LIN-Q and GBR-Q show the worst predictive performance in most cases, indicating that a median quantile prediction could not generalise well on unseen test sets.

SPLINE has the lowest error among the statistical models in several cases (underlined in Table 4), in particular, in models using vulnerability as predictors. Surprisingly, LIN performs well out-of-sample on combined volatility and vulnerability information. This implies a complex non-linear patterns can be approximated by the standard LIN. Both LIN and SPLINE are robust counterparts of ML techniques, with only a 1% marginal difference relative to the best-performing ML techniques. However, SPLINE has the extra benefit of unveiling the underlying non-linear structures, which can be helpful for a more in-depth and nuanced risk analysis (for details refer to Section 3.4).

3.3. Linear regression: risky volatile situations

Table 5 reports the marginal effects of linear regression in the three types of model setup[1]. The following discussion highlights risky transactional patterns having significant statistical effect on (high/low) volatility that may relate to financial difficulty.

[Table 5 about here.]

The significant positive coefficients of lagged volatility (Y lag1, Y lag2) in Type 1 model indicate the persistence of past volatility for future predictions. The larger positive effect of Y_lag1 than Y_lag2 shows a diminishing effect of the past values, where conditions at the most recent time point has the strongest impact on the near future.

In Type 2 model, the significant covariates reveal which aspects of vulnerability are relevant for volatility prediction. Covariates indicating financial buffer shortage such as shifting from positive to negative balance (X5), lower month end balance than inflow (X7) and reduced account balance (X8) are positively associated with volatility. This suggests that low financial capacity often leads to unstable cash flows. High volatility is associated with sudden changes in balance amount (X4), which implies that financial behaviour fluctuate due to the occurrences of unexpected events. A positive relationship between overdraft usage (X9) and volatility indicate that increased use of overdraft (and possibly other

[1] Table 5 shows the selected covariates after the forward features selection procedure. The same set of covariates are used in all models.

types of debt) leads to increased instability. Low spending capability with lesser days of outflow transactions (X28) and frequent decrease in spending activities (X21, X30) also relates to high volatility. People who put a lower priority on fixed and living expenses (X35, X36, X42, X51) as well as those who participate in gambling more frequently (X55) tend to be more volatile. This suggests that reductions in financial capacity and unhealthy addictions may lead to increased cash flow fluctuations.

Yet certain aspects of financial vulnerability can also lead to low volatility, such as frequent inability to meet financial obligations (X63, X69) and extensive overdraft usage (X12). This may mean that people are hitting the bottom of their capacity (e.g. an overdraft limit) and with nowhere to go, will exhibit lower volatility and restrict spending behaviour. Although vulnerability risk (X93) is not a significant predictor for volatility, the negative association shows that people under vulnerable circumstances tend to limit their cash flow activities to keep up with living.

In Type 3 model, several transactional behaviour in Type 2 become non-significant (X4, X9) or shift to the opposite effect (X17). This is probably due to their strong correlations with the volatility covariates which mask their effect on future volatility. Most of the vulnerability covariates have reported statistical significance in Type 3, implying that transactional patterns contain additional information to explain future volatility.

3.4. Spline regression: varying impact levels of transactional behaviour on volatility

This section interprets several covariates as representative examples (from Type 2) to examine how changes in transactional behaviour impact financial volatility. We analyse the marginal effects from spline regression to highlight the relationships not captured by linear regression and to emphasise the varying effect of the non-linear structure.

The marginal effects of overdraft use on volatility (Fig 2) can be described by the following two scenarios. Occasional overdraft use has a stronger impact on increasing volatility than a regular one (Fig 2a). Consistent reliance on heavy overdraft reduces volatility substantially, but temporary use increases volatility slightly (Fig 2b). The increasing patterns in both figures indicate a higher risk of daily life disruption from accidental overdrafts, possibly due to unforeseen events. On the other hand, persistent use of heavy overdrafts due to limited financial capacity leads to low volatility.

[Figure 2 about here.]

The non-monotonic positive trend in Figure 3a shows a rapid increase in financial volatility from income loss. Larger income shocks impact more strongly on financial stability, and therefore bring a sharper rise in volatility. We can notice a steeper gradient on the left than on the right-hand side, indicating unanticipated events to lose income are more disruptive to financial stability. For Figure 3b, the initial part of decreasing slope suggests smaller increases in spending on groceries steadily reduces volatility. However, after a certain point, further increases produce an opposite effect and volatility sharply increases.

[Figure 3 about here.]

The decreasing pattern in Figure 4a shows that volatility drops steadily with the increasing number of months with lower spend on electricity and gas, which is logical - smaller values on spending imply less variation. However, there is an almost flat section at the right-hand side, implying that volatility stabilises for very high values of number of months with lower spend on electricity and gas. After a certain level, cutting on utilities has very little effect on volatility.

Figure 4b illustrates that volatility drops sharply at lower values of vulnerability, and then increases steadily with the increase of vulnerability risk. It shows a slightly steeper rise at high vulnerability risk values. The graph summarises the complex relationship between volatility and vulnerability, there isn't a simple linear pattern, the pattern varies depending on the level of vulnerability, and the next section is going to explore this in more detail.

[Figure 4 about here.]

3.5. Target risk groups

The non-linear effects between volatility and vulnerability risk reveal several potential target groups that may need different approaches from modelling and customer management points of view. A potential segmentation can be based on Figure 4(b) with splits done on the values of vulnerability index, e.g. up to 0.4 there will be low risk customers with low vulnerability. One can also subset this group to accommodate the high/low volatility segments. However, in general, this group will require mostly monitioring without the need for interventions. High volatility sub-set may require a different modelling approach in forecasting cash flows. From 0.4 to 0.7, the customers can be defined as medium-risk. And finally, the highest risk group are those accounts with high vulnerability risk (0.7+) and high volatility. These accounts present the risk of deteriorating financial circumstances, coupled with unstable behaviour which complicate the prediction for future planning and interventions.

Special attention should also be given to the medium risk group, where the accounts have medium vulnerability risk paired with relatively high volatility. This group should be monitored very closely for the signs of further deterioration. For both the high and medium risk groups, inspecting the transactional behaviour to interpret the source of risk should assist in finding the mitigation strategies.

For accounts with low or even no vulnerability risk, monitoring the transactional patterns to identify risky drivers of (low/high) volatility serves as a pre-emptive measure to prevent vulnerability. Vulnerability is a complex personal financial risk, where even people currently with low risk levels can face financial shocks and become vulnerable due to external factors. Hence, the transparent explanation of the non-linear structures is important in identifying vulnerability-prone characteristics. Risky transactional patterns that have a stronger impact on volatility, such as, unusual use of overdraft or income shock, can be an indication of being more vulnerable to future uncertainties.

3.6. Marginal effects vs ALE

Despite SPLINE showing a competitive predictive performance, machine learning algorithms have a slight edge in Type 3 models, therefore, it is important to consider the ways their output can be interpreted. We compare the SPLINE's marginal effects with the ALE plots' post-hoc explanations obtained from XGB. Based on several illustrative examples, we point out similarities and differences in non-linear patterns as reported in the two models. Then, we highlight the effectiveness and potential pitfalls of SPLINE and ALE, in capturing the underlying non-linearities.

Both SPLINE and ALE express similar non-linear shapes in most covariates, as reported in Figure 5. Although the captured covariates' effects are not identical, both models show a high resemblance in terms of the overall trend (non-monotonic increase/decrease) and the presence of inflection points to indicate changes in volatility risk level. SPLINE marginal effect turns out to portray 'smoother' curves than ALE, due to the ALE approach to compute the local effects in grids. Since SPLINE and XGBoost have completely different training procedures, the certain degree in varying monotonicity portrayed here is expected.

[Figure 5 about here.]

On the other hand, there are several covariates where SPLINE and ALE suggest different interpretations. Referring to Figure 6, for example, (i) ALE illustrates a similar increasing trend with SPLINE at low values of X5, but continues to increase instead of decreasing, after the turning point; (ii) SPLINE presents an increasing pattern in X9 and U-shape in X93, whereas ALE has a stepwise increasing shape for X9 and X93. We provide the following potential reasons to explain the different non-linear structures. First, it might be merely due to the ability of each model to capture the patterns during model training. Second, focusing on the 'mini-bars' in the x-axis of ALE plots, we notice that covariates showing differences have skewed distributions, causing the problem of insufficient data instances to properly express the hidden patterns.

[Figure 6 about here.]

The high similarity between the non-linear patterns expressed by SPLINE and ALE confirms that both methods are effective in discovering hidden structures of the covariates. It means that it is possible to obtain powerful and interpretable predictions, irrespective of preferences for either statistical parametric techniques or non-parametric machine learning. However, SPLINE's marginal effects have an advantage of providing transparent explanations of how the changes in the transactional patterns are expected to impact changes in financial volatility that are directly imbedded in model estimation and are similar to standard regression interpretation. While ALE also gives appropriate interpretations, the post-hoc approach describes how the covariates affect the predictions on average over specified intervals, but the interpretation of the effect is still local and depends on intervals chosen.

The contrasting patterns denoted between SPLINE and ALE bring to the attention potential pitfalls even when we use marginal effects for white-box explanations. As observed from ALE, skewed distributions can distort covariates' interpretation because of low frequencies in certain ranges of the distribution. Analogously, the marginal effects for these covariates may not be completely reliable due to inadequate data points at the tail of the distribution. Thus, the interpretations of these covariates should come along with a flag, to be mindful of potential misleading shapes. Users can then proceed with further investigations, if necessary.

4. Conclusion

This study explores an approach to predict the account volatility for assessing the personal financial risk with stability in cash flow behaviour from (i) the past volatility, (ii) a wide range of vulnerability-related transactional patterns, and (iii) the vulnerability index.

Both past volatilities and vulnerability are important predictors of future volatility. Despite a modest increase in predictive power, vulnerability predictors contain valuable details to reveal the specific circumstances behind unstable future cash flows. This provides the ability to separate high and low financial risk which could not be done when only past volatilities are the covariates. We discover several risky volatile situations. Detrimental high volatility is related to low financial capacity due to the lack of financial buffer, sudden changes in the balance, financial instability from excessive debt, low spending capability, inconsistent financial practices, and unhealthy addictions. On the other hand, harmful low volatility is related to reduced transactional level that may also signal financial problems.

Although the vulnerability index does not have significant effect on future volatility, the non-linear impact of vulnerability index on volatility provides the basis for segmenting the accounts into different target risk groups. To ensure that the past vulnerability will not persist to disrupt future cash flow stability, financial institutions should understand the source of risk and set up mitigation strategies. To

prevent further deterioration of vulnerability in the low-risk group, we should monitor the presence of risky volatile behaviour that are prone to vulnerability.

We show that high predictive accuracy can be achieved with several models, giving users a choice of algorithms depending on their preferences. We also demonstrate how the outputs from ML models can be interpreted. The similar patterns illustrated from the spline regression's marginal effects and accumulated local effects plots verify that spline regression can handle non-linearities, as good as the machine learning model. Nonetheless, spline regression is advantageous in giving transparent explantions which are part of the model training in contrast to a post-hoc estimation from the predicted values in ALE.

Despite its insights into the complex relationship between volatility and vulnerability, this study is not without limitations. First, the OB data used in our experiment provide transactions at the account level instead of individual level. Hence, further research can extend the volatility risk assessment to multiple accounts at individual level. Second, the OB data provides the most recent 12-month transactional records, limiting the current experiment setup to a short-term risk evaluation where further investigations would be required to understand the long-term impact of transactional behaviour on volatility. Third, the risk assessment framework is built solely on OB data which might not cover the other financial aspects such as the credit and arrears status or ownership of financial assets. Potential future works can include additional data into the existing framework or extend the current cross-sectional approach to a panel study to track dynamic financial behaviour.

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Appendix A. List of covariates

[Table 6 about here.]

Appendix B. Principal Component Analysis

Given a set of correlated variables, PCA assumes there exists an underlying latent structure to represent the original variables as new uncorrelated latent variables, known as principal components (PC). The PCs are linear functions of the input data which are estimated in a way to successively maximise the variance (information) contained in the original variables. Selecting an optimal number of PCs reduces dimensionality of the data and gives the best weighted combinations of the input attributes to form a single composite index.

The correlation matrix of a standardised attributes is denoted as $\mathbf{M}_{a\times a}$. The PCA decomposition on $\mathbf{M}$ to obtain the eigenvectors and eigenvalues is equivalent to a linear transformation of the original variables. The eigenvector-eigenvalue pairs follow a successive pattern such that the first pair has the largest eigenvalue to capture the largest variation (most information retained) in the direction of the paired eigenvector, followed by the second largest eigenvalue in orthogonal direction for the next largest variation, and so on. For $a = 1,...,A$ number of attributes, PCA obtains $l = 1,...,L$ principal components PC_l which comprises the l-th eigenvalue λ_l and l-th eigenvectors $\psi_{l,a}$ for each attribute a. Each PC_l represents a weighted linear combination of the a attributes with the weights defined from $\psi_{l,a}$. The percentage of explained variance by each PC can be obtained from the eigenvalues with $\frac{\lambda_l}{\sum_{l=1}^{L}\lambda_l}$.

The composite index (CI) is computed from an optimal κ number of PC. The percentage of variance accounted by each PC is examined to ensure the number of selected PCs sufficiently retain information from the input attributes, and also effectively discard unnecessary noise. For $i = 1,...,n$ accounts, and the input instance $D_{i\times a}$ with a dimensions of attributes, the CI for each account can be expressed as the weighted combinations of the PCs,

$$\mathrm{CI}_i = \frac{\sum_{l=1}^{\kappa}\sum_{a=1}^{A}\lambda_l(\phi_{l,a}D_{i,a})}{\sum_{l=1}^{\kappa}\lambda_l}, \tag{B1}$$

such that the weights, w_a can be interpreted as the relative importance of each attribute a to the final CI, denoted as,

$$w_a = \frac{\sum_{l=1}^{\kappa}\lambda_l\psi_{l,a}}{\sum_{l=1}^{\kappa}\lambda_l}. \tag{B2}$$

Appendix C. Models to be compared

C.1. Linear regression

In linear regression (LIN), the target variable is expressed as a linear function of the covariates $y_i = x_i\beta + \epsilon_i$. The parameters are estimated with Least Square estimator which minimises the sum of squared residuals, $\sum_{i=1}^{n}|y_i - x_i\beta|^2$.

C.2. Linear quantile regression

Linear quantile regression (LIN-Q) estimates the conditional quantiles, instead of conditional mean, to capture non-constant effects of covariates on the target variable. The regression equation is expressed as $y_i = x_i\beta_q + \epsilon_i$, where now β_q represents the parameters to be estimated for different q quantile values. A quantile of $q = 0.5$ is a special case for median regression. The parameters are obtained by minimising an asymmetric error loss function,

$$Q_n(\beta_q) = \sum_{i;y \geq x_i\beta}^{n} q|y_i - x_i\beta_q| + \sum_{i;y<x_i\beta}^{n} (1-q)|y_i - x_i\beta_q|. \quad \text{(C1)}$$

C.3. Spline regression

Spline function is effective in modelling non-linear and irregular shapes to enhance credit default predictions and discover underlying consumers' behaviour (Djeundje & Crook, 2019a, 2019b; Giordani et al., 2014; Luo et al., 2016). Spline is constructed from continuous piecewise polynomial functions to mathematically reproduce flexible shapes. Knots are points located within the data range to join the segments of adjacent polynomials together. We focus on B-spline or spline basis functions due to its computational advantages as discussed in Green and Silverman (1993).

Spline regression (SPLINE) performs regression on the spline basis functions. Given $i = 1,2,...,n$ accounts and x_i as a $1 \times p$ vector of covariates, the target variable is expressed as $y_i = \sum_{j=1}^{p} f_j(x_{i,j}) + \epsilon_i$ where ϵ_i is the independent and identically distributed error term of $\epsilon_i \sim N(0,\sigma^2)$, $f(.)$ is the spline function to be estimated that transforms the j-th covariate, for $1 \leq j \leq p$ covariates, into a non-linear space to model for complex patterns. Each covariate is represented as a linear combination of B-splines

$$f(x) = \sum_{\theta=1}^{m+k} \beta_\theta g_\theta(x), \quad \text{(C2)}$$

where $B_\theta(x)$ are the B-splines with m-th order over the knot set of $t_1 \leq t_2 \leq t_3 ... \leq t_k$, θ is the index of B-splines, and β_θ are the splines coefficients to be estimated with the least square estimator.

The specification of SPLINE requires cautious selection of the spline order as well as the number and position of the knots. Higher polynomials order and number of knots provide more flexibility to fit non-linear pattern but poses the risk of overfitting. We focus only on quadratic and cubic splines since going beyond cubic specification is usually unnecessary (Hastie, Tibshirani, & Friedman, 2009). To select the appropriate number of knots, we manually examine the root mean squared error measure from ten-fold cross validations across $k = [1,20]$, and pick the final k which gives the lowest error measure. The knots are located based on the quantile values. Quadratic B-spline is the final specification used because it has lower cross validation errors than cubic B-spline.

C.4. Random forest

Random forest (RF) is a collection of unpruned regression trees with the bagging technique introduced by (Breiman, 2001). RF injects diversity during the training process via two approaches. First, each tree is fitted on a bootstrapped sample of the original data which is independently and identically distributed to the others. Second, the choice of best split at each tree node is a random subset of m features instead of the full p features. Both approaches increase the randomness and reduce the

correlation among the trees. RF aggregates the result by taking the mean of the predictions from all regression trees.

C.5. Gradient boosting quantile regression

Gradient boosting machines (GBM) Friedman (2001) is an ensemble of weak regression trees in a sequential manner. In each iteration, a new model is constructed with respect to the pseudo residuals from the gradient of an arbitrary differentiable loss function. The ensemble is updated by adding the new model into preceding trees. Gradient boosting quantile regression (GBR-Q) focuses on conditional quantile in the tree learning procedure by minimising the asymmetric loss function in Equation (C1) instead of the conventional squared error loss.

C.6. Extreme gradient boosting regression

Extreme gradient boosting (XGB) is an advanced implementation of the GBM system (Chen & Guestrin, 2016). The regression tree ensemble is updated in each iteration t by minimising the objective function $L^{(t)}$,

$$L^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y_i}^{(t-1)} + f_t(x_i)) + \Omega(f_t) \quad . \tag{C3}$$

Two distinct differences between XGB with GBM are (i) XGB includes an additional regularisation term in the objective function and (ii) the tree learning process of XGB employs Taylor expansion to take up to the second derivative of the loss function, instead of only optimising the first derivative as in GBM. Both properties are advantageous to control model complexity and prevent overfitting.

C.7. Multilayer perceptron network

The Multilayer Perceptron Neural Network (MLP) comprises of one input layer, a number of hidden layers and one output layer Bishop (1995). Hidden layers contain neurons as the medium to connect the entire network by input processing and output generation. Given a MLP with q layers, the output vector of neurons from layer $l = \{1,2,...,q\}$ for account i is denoted as $Z_i^{(l)}$ where the covariates act as the input for the first layer.

$$Z_i^{(l)} = f(W^{(l-1)} Z_i^{(l-1)} + b^{(l-1)}), \quad Z_i^{(1)} = x_i. \tag{C4}$$

The parameter $W^{(l)}$ is a weight matrix to connect neurons in the current layer with the previous one and $b^{(l)}$ is the intercept to increase or decrease the weighted linear sum. The neurons generate the output for each layer with the rectified linear unit activation function $f(.) = max(0,x)$. The forward propagation process transmits the output from one hidden layer to be the input for the subsequent layer, until the output layer is reached. The learning process update the parameters W and b via repeated forward and backward propagations by minimising the squared error loss function.

C.8. Deep belief network

Deep belief network (DBN) is a class of deep neural network constructed from a stack of subnetworks, known as Restricted Boltzmann Machine (RBM) (Hinton, 2009). RBM is an undirected neural network such that the visible units are connected to the hidden units but there are no visible-to-visible or hidden-to-hidden connections.

The DBN training process starts from the layer-by-layer RBM unsupervised learning. The first RBM layer takes the input data vector. Each RBM layer aims to model the input data distribution as close as possible by maximising the likelihood of the training data. Hidden units in each layer act as features detector to capture underlying complex relationships via weighted connections with the visible units. The learned features from the first RBM layer are then used as the input for the second, and subsequently until the last layer. Once the training of the RBM layers are complete, DBN proceeds to the fine-tuning process to update the network parameters with the error backpropagation algorithm.

Appendix D. Model explainability

The marginal effects from spline regression explains how financial volatility (target variable) changes when a specific transactional behaviour (covariate) changes. For each covariate, we illustrate a marginal effect plot to examine the impact of changes in the covariate's value on the prediction while holding all other covariates constant.

Accumulated local effects (ALE) plots visualise the influence of a covariate on the average model predictions (Apley & Zhu, 2020). Since the transactional behaviour are correlated to one another, partial dependence plots and conditional expectation plots are severely biased. To correct for this, ALE works on estimating local differences in predictions over a partitioned conditional distribution, averaging and accumulating them, which isolates the effects of a specific covariate. Thus, we focus on ALE to provide unbiased estimations of the non-linear relationships. The range of each covariate $x_{i,j}$ is partitioned into K intervals with the a set of grid points $\{z_{k,j}\}_{k=0}^{k=K}$.
The $z_{k,j}$ are chosen as the $\frac{k}{K}$ quantile of the covariate's distribution where $z_{0,j}$ is selected just below the smallest observation and $z_{K,j}$ selected as the largest observation. Hence, we obtain K intervals indexed by $k_j(x)$ where the k-th interval is denoted as
$N_j(k) = (z_{k-1,j}, z_{k,j}]$ and the number of observations in each interval is denoted as $n_j(k)$ such that $\sum_{k=1}^{K} = n$. The ALE estimation is expressed as

$$ALE_j(x) = \sum_{k=1}^{k_j(x)} \frac{1}{n_j(k)} \sum_{i:x_{i,j} \in N_j(k)} [f(z_{k,j}, x_{i,\setminus j}) - f(z_{k-1,j}, x_{i,\setminus j})] \quad . \qquad \text{(D1)}$$

The inner sum represents the local effect from all observations in a specific interval which is computed by taking the difference between the predictions when x_j equal to the upper limit ($z_{k,j}$) and x_j equal to the lower limit ($z_{k-1,j}$) of the interval. The sum of prediction differences is divided with the number of observations within each interval to obtain the average local effects, which is then accumulated in order (the outer sum). Hence, ALE of a covariate with a value lies in the k-th interval is the sum of the effects from the first up to the k-th interval. ALE is mean centered, thus it is interpreted as the main effect of a covariate (at a certain value) relative to the average prediction.

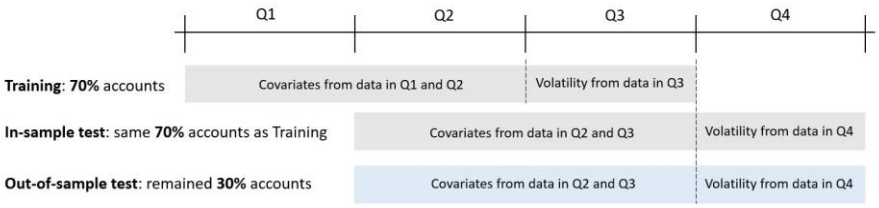
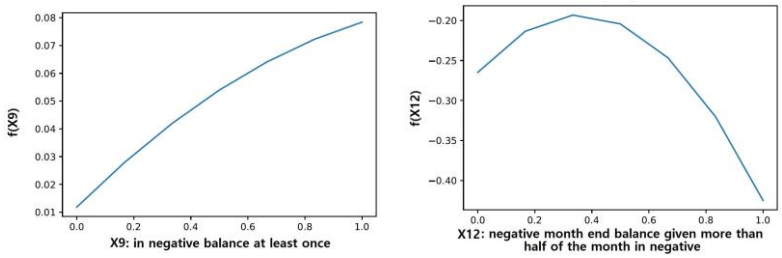
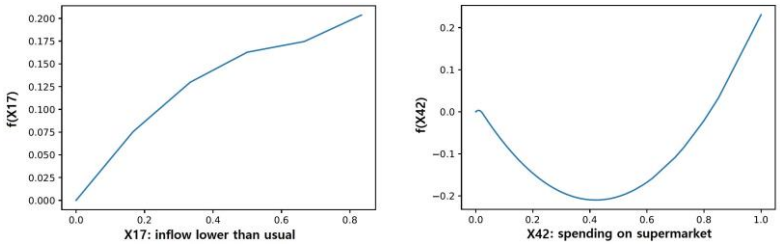


Figure 1. Training and test data split



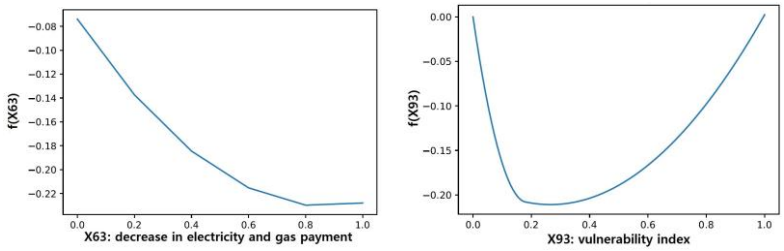
(a) X9 (b) X12

Figure 2. Marginal effects of X9 and X12



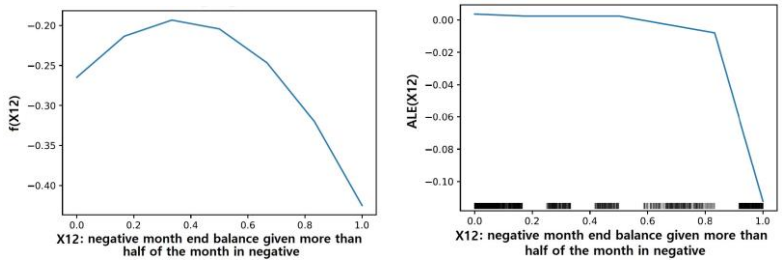
(a) X17 (b) X42

Figure 3. Marginal effects of X17 and X42

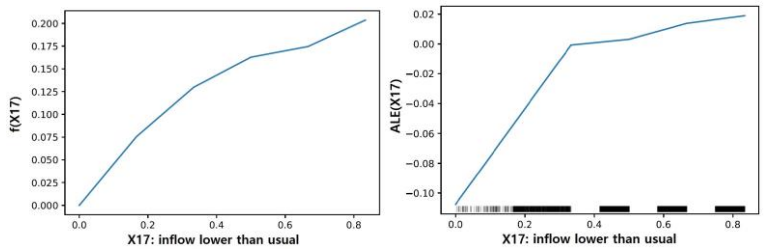


(a) X63 (b) X93

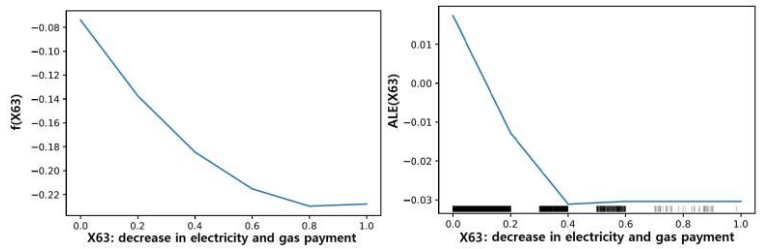
Figure 4. Marginal effects of X17 and X42



(a) SPLINE: X12 (b) ALE: X12

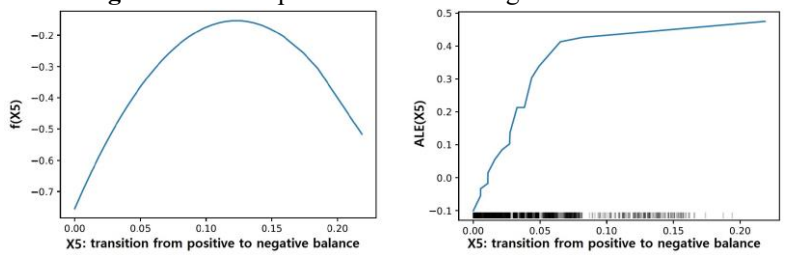


(c) SPLINE: X17 (d) ALE: X17

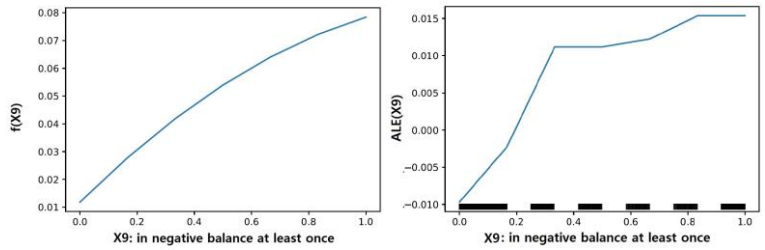


(e) SPLINE: X63 (f) ALE: X63

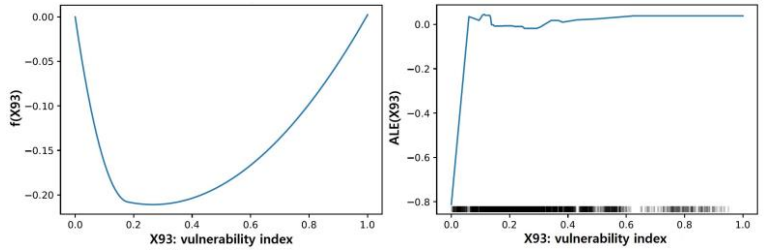
Figure 5. Similar patterns between marginal effects and ALE



(a) SPLINE: X5 (b) ALE: X5



(c) SPLINE: X9 (d) ALE: X9



(e) SPLINE: X93 (f) ALE: X93

Figure 6. Different patterns between marginal effects and ALE

Table 1. Description of raw transactional records

Variable	Description
Transaction Date	Date when the transaction occurs
Description	Details of the transaction's counterparty
Transaction Type	Type of transaction (Credit: inflow/ Debit: outflow)
Amount	Transaction amount
Category	Income or expenditure categories*
End balance	Remaining balance after the transaction**

*assigned by the categorisation engine of the data provider
**calculated based on the balance amount in the latest day of the transactional record

Table 2. Summary of covariates and types of model setup

		Included: ✓		
Aspect	Covariate	Type 1	Type 2	Type 3
(1) Volatility		✓		✓
volatility lag 1	Y lag1			
volatility lag 2	Y lag2			
(2) Vulnerability circumstances			✓	✓
(A) Past transactional patterns				
(i) Balance				
daily	X1-X5			
monthly	X6-X8			
distress	X9-X12			
lowest balance	X13-X16			
(ii) Inflow	X17-X25			
(iii) Outflow	X26-X34			
(iv) Spending on specific categories	X35-X92			
(B) Vulnerability index	X93			

Table 3. Principal Component Analysis estimates

Dimensions	PC1	PC2	PC3	Weights*
cv balance	0.1147	0.9934	0.005298	0.3915
cv inflow	0.7027	-0.07734	-0.7073	0.3619
cv outflow	0.7022	-0.08483	0.7069	0.3592

eigenvalues	1.655	0.9914	0.3543
% explained variance	0.5515	0.3304	0.1181

*computed from PC1 and PC2

Table 4. Predictive performance

	(1) Volatility				(2) Vulnerability				(3) Volatility and vulnerability			
	(2) in-sample		out-of-sample		in-sample		out-of-sample		in-sample		out-of-sample	
Model	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Statistical												
LIN	0.7938	**0.6204**	0.8055	0.6356	0.8117	0.6357	0.8079	0.6366	0.7858	0.6161	0.7909	0.6259
LIN-Q	0.8144	0.6295	0.8190	0.6395	*0.8281*	*0.6407*	*0.8157*	0.6339	0.8008	0.6232	0.7993	0.6295
SPLINE	0.7944	0.6223	**0.8020**	0.6365	0.8060	0.6314	0.8051	0.6347	0.7898	0.6207	0.7957	0.6304
Tree ensembles												
RF	*0.8508*		*0.6650*		*0.8776*		*0.6892*		**0.7957**	**0.6215**	**0.8026**	
0.6339	**0.7787**	**0.6121**	**0.7903**	0.6265								
GBR-Q	0.8113	0.6292	0.8130		0.6392	0.8198	0.6384		0.8121	**0.6325**	*0.8020*	
0.6249	*0.8053*	*0.6331* XGB			**0.7916**	0.6205	0.8021		0.6365	0.8042	0.6291	
0.8053	0.6351	0.7898	0.6191		0.8004	0.6328						
Neural network												
MLP	0.7940	0.6222	0.7996		**0.6338**	0.8096	0.6340		0.8059	0.6365	0.7834	
0.6164	0.7918	0.6284										
DBN	0.7940	0.6212	0.8090		0.6396	0.8105	0.6313		0.8080	*0.6397*		
0.7854	0.6183	0.7892	**0.6251**									

Table 5. Linear regression estimates

Covariate	Description	(1) Volatility Coefficient	(2) Vulnerability Coefficient	(3) Volatility & vulnerability Coefficient
(intercept)		-0.0008	-0.3302***	0.0425
Y lag1	volatility index in the previous quarter	0.2998***		0.2330***
Y lag2	volatility index in the previous two quarter	0.2433***		0.1549***
X2	consecutive days in same balance amount		1.564***	0.9583***
X5	transition from positive to negative balance		5.831***	3.576***
X4	extreme high or low balance amount		2.396***	0.0030

X7	month end balance less than month inflow	0.0976**	0.0774**
X8	month end balance less than month open balance	0.3301***	0.1829***
X9	take at least one overdraft in a month	0.1654**	0.0447
X12	negative month end balance where more than half of the month is in negative	-0.2360***	-0.0905*
X17	inflow lower than usual	3.149***	-0.1675***
X24	decrease in days with inflow	0.2305***	0.1111**
X28	days with outflow transactions	-0.7765***	-0.4204***
X21	decrease in number of outflow transactions	0.2849***	0.1993***
X30	continuous decrease in outflow amount	0.1338***	0.1180***
X35	spending on rent payment	-0.4695***	-0.2666**
X36	spending on telephone and tv	-1.008***	-0.6698***
X42	spending on supermarket	-0.753***	-0.4246***
X45	spending on convenience store	1.114***	1.122***
X51	spending on loan	-0.6308***	-0.5155***
X55	spending on gambling and gaming	0.5665***	0.5032**
X63	decrease in electricity and gas payment	-0.3024***	-0.2146***
X69	decrease in telephone and tv payment	-0.1822***	-0.0985**
X93	vulnerability	-0.0086	-0.0782

***significant at $\alpha = 0.001$ **significant at $\alpha = 0.01$*significant at $\alpha = 0.05$

Table 6.: List of covariates

Covariate	Description
(1) Balance (a) overall summary day balance	
X1	in negative balance
X2	consecutive days in same balance amount
X3	move towards a worse negative balance
X4	extreme high or low balance amount
X5	transition from positive to negative balance
month balance X6	month inflow less than month outflow
X7	month end balance less than month inflow
X8	month end balance less than month open balance
distress situation X9	in negative balance at least once

X10	negative month end balance
X11	larger negative month end balance than a negative month opening balance
X12	negative month end balance where more than half of the month is in negative
(b) decreasing trend	
X13	decrease in month largest negative balance amount
X14	continuous decrease in month largest negative balance amount
X15	decrease in minimum balance amount
X16	continuous decrease in minimum balance amount
(2) Inflow	
(a) overall summary	
X17	inflow lower than usual
X18	extreme high or low inflow amount
X19	days with inflow transactions
(b) decreasing trend	
X20	decrease in inflow amount
X21	continuous decrease in inflow amount
X22	decrease in number of inflow transactions
X23	continuous decrease in number of inflow transactions
X24	decrease in days with inflow
X25	continuous decrease in days with inflow
(3) Outflow	
(a) overall summary	
X26	outflow higher than usual
X27	extreme high or low outflow amount
X28	days with outflow transactions
(b) decreasing trend	
X29	decrease in outflow amount
X30	continuous decrease in outflow amount
X31	decrease in number of outflow transactions
X32	continuous decrease in number of outflow transactions
X33	decrease in days with outflow
X34	continuous decrease in days with outflow
(4) Spending categories (a) overall summary	
fixed costs	
X35	spending on rent payment
X36	spending on telephone and tv
X37	spending on insurance
X38	spending on electricity and gas
X39	spending on property and council tax X40 spending on subscriptions and renewals
living costs	
X41	spending on eating out
X42	spending on supermarket X43 spending on retail

X44 spending on online retail
X45 spending on convenience store
X46 spending on clothing
X47 spending on vehicle fuel X48
spending on public transport

debts
X49 spending on mortgage payment
X50 spending on vehicle loan
X51 spending on loan
X52 spending on credit card
X53 spending on interest X54 spending
on overdraft charges

others
X55 spending on gambling and gaming
X56 spending on savings
X57 spending on healthcare and medical
X58 spending on transfer payments
X59 spending on leisure and entertainment
X60 cash withdrawal amount
(b) decreasing trend
fixed costs
X61 decrease in rent payment
X62 continuous decrease in rent payment
X63 decrease in electricity and gas payment
X64 continuous decrease in electricity and gas payment
X65 decrease in insurance payment
X66 continuous decrease in insurance payment
X67 decrease in property and council tax payment
X68 continuous decrease in property and council tax payment
X69 decrease in telephone and tv payment
X70 continuous decrease in telephone and tv payment
X71 decrease in subscriptions and renewals payment
X72 continuous decrease in subscriptions and renewals payment

debts
X73 decrease in mortgage payment
X74 continuous decrease in mortgage payment
X75 decrease in loan payment
X76 continuous decrease in loan payment
X77 decrease in vehicle loan payment
X78 continuous decrease in vehicle loan payment
X79 decrease in credit card payment
X80 continuous decrease in credit card payment
X81 decrease in interest payment
X82 continuous decrease in interest payment
X83 decrease in overdraft charges payment
X84 continuous decrease in overdraft charges payment

others
X85 decrease in gambling and gaming
X86 continuous decrease in gambling and gaming

X87	decrease in savings
X88	continuous decrease in savings
X89	decrease in healthcare and medical expenses
X90	continuous decrease in healthcare and medical expenses
X91	decrease in transfer payments
X92	continuous decrease in transfer payments
(6) vulnerability	
X93	vulnerability risk index a composite index constructed by PCA from the following numeric attributes: (i) total healthcare expenditure (ii) total income loss (iii) total amount of benefits received (iv) debt-to-inflow ratio (v) debt amount (vi) outflow-to-inflow ratio (vii) buffer-to-outflow ratio (viii) expenses on social activities or hobbies