Identifying Deviations in Payment Behavior Using Participant Profiles in TARGET2

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IDENTIFYING DEVIATIONS IN PAYMENT BEHAVIOR USING PARTICIPANT PROFILES
Co-Authors and Disclaimer

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Agenda

1) Introduction
2) Data
3) Methodology
4) Results
5) Conclusion
6) Discussion

Motivation

- Understanding participant‘s payment behaviour is relevant for several purposes (liquidity distribution, risk identification…).
- In particular, days with unusual payment activity could indicate a risk event.

Main idea:

Compare the daily intraday payment behavior with the normal behavior.

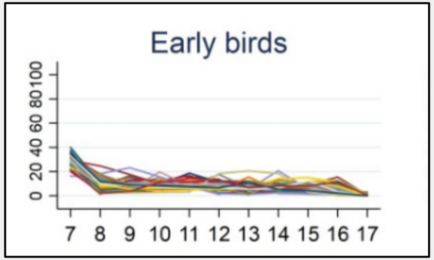
What are goal and criteria of the comparison?

How to deal with the various dimensions of „behavior“?

What is normal without a label on the data?
Is there enough stability to find normality?

INTRODUCTION
Definitions

- **Intraday payment pattern of a participant:** The relative share in volume of payments submitted by the participant in each of the 11 hours of the TARGET2 business day at daily level
- **Intraday payment profile:** General rule describing the pattern of a participant
  - The profiles have been deviated using a multiple cluster procedure applied to yearly average patterns in order to identify similarities across participants
    (Presented at BoF seminars in 2018 and 2019, Glowka 2020)



Average longer term patterns of participants forming a cluster…

…translated into a rule describing the profile

"Between 20% and 40% of the daily transactions are introduced in the **first business hour**. In addition, this is the maximum **for the day."**

INTRODUCTION
Profiles (a reminder)

Payment Profiles	Main characteristics
Not active (0)	No payments submitted on that day.
Early Birds (1)	Between 20% and 40% of the daily transactions are introduced in the first business hour. In addition, this is the maximum for the day.
Extreme Early Birds (2)	The maximum of the day and more than 40% of the daily transactions are introduced in the first business hour.
Second Wave (3)	More than 20% of the daily transactions are introduced between 8:00h and 9:00h. This is also the maximum for the day.
Third Wave (4)	More than 20% of the daily transactions are introduced in the third business hour and, in addition, this is also the maximum for the day.
Long Sleepers (5)	The maximum for the day and more than 20% of the daily transactions are introduced between 10:00h and 11:00h.
Late morning Payers (6)	More than 20% of the daily transactions are introduced in the fifth business hour. In addition, this is also the maximum for the day.
Noon Payers (7)	More than 20% of the daily transactions are introduced between 12:00h and 13:00h and, in addition, this is also the maximum for the day.
Time-independent Payers (8)	The participants with these profiles distributed their payment activity evenly over the day with fewer transactions in the morning or evening. No one-hour interval exceeds 20% of the transaction share.
Tea-time Payers (9)	The transaction volume share increases over the day and reaches a maximum between 15:00h and 17:00h. In addition, the transaction volume share remains usually below 20% over the day.
Late Payers (10)	The maximum and more than 20% of the daily transactions are introduced in the afternoon between 13:00h and 17:00h.

Main idea revisited

Main idea:

Compare the daily intraday payment behavior with the normal behaviour.

Observed pattern or respective profile is different than expected pattern or respective profile.
→ When is the difference significant?

Intraday pattern or respective profile as a meaningful reduction of complexity. ☑

Reference/expected pattern or respective profile.
→ How to define this?

DATA
Basic Data Set

Data Basis

Selection

Preparation

TARGET2 transactions

- ✓ 01/2011 until 03/2022 (closure of TARGET2)
- ✓ Customer, Interbank and CLS payments
- ✓ Day-time settlement cycle transactions
- ✓ Large participants (at least 0.05 % transaction volume on TARGET2 in 2017)
- ✓ Remove disabled periods of participants

By day and participant
- Pattern
- Profile

DATA
Reference profile and deviations

Defining normality

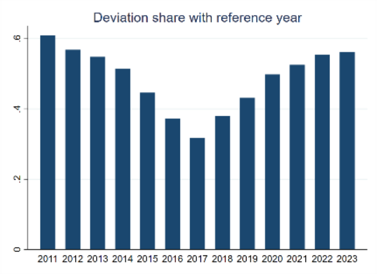
- "Normal" behaviour might be subject to persistent changes
- Using a static reference period leads to time dependency and loss of significance for other explanatory variables

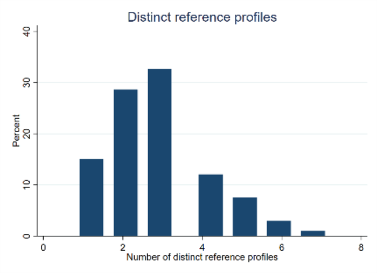
➔ Use of rolling window approach for reference period

Dealing with complexity

- Calculation of an average behaviour (e.g. mean value for the relative share in each hour interval) leads to a potential loss of information

➔ Use of the dominant profile, the most frequent daily payment profile in the reference period





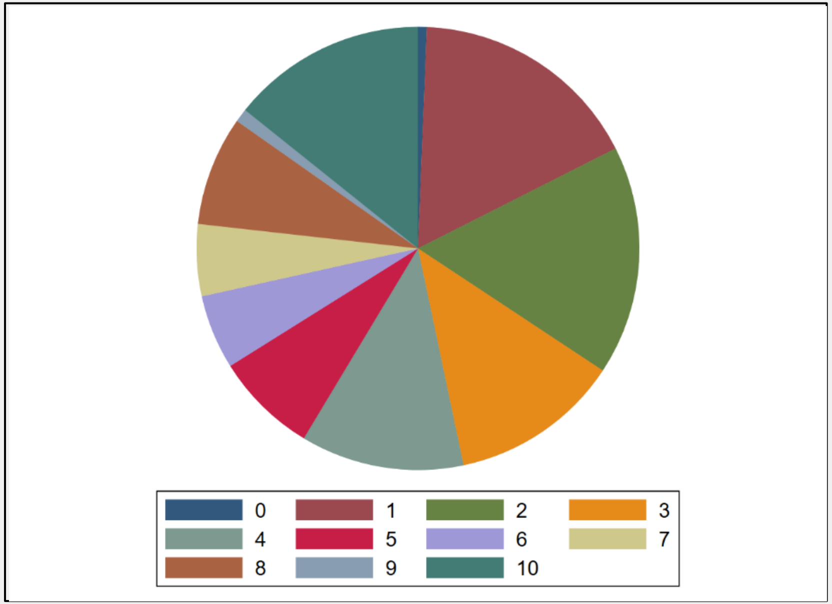
Reference profile = The most frequent profile in the previous 250 business days[1] ☑

Deviation = Daily Profile != Reference Profile[2] ☑

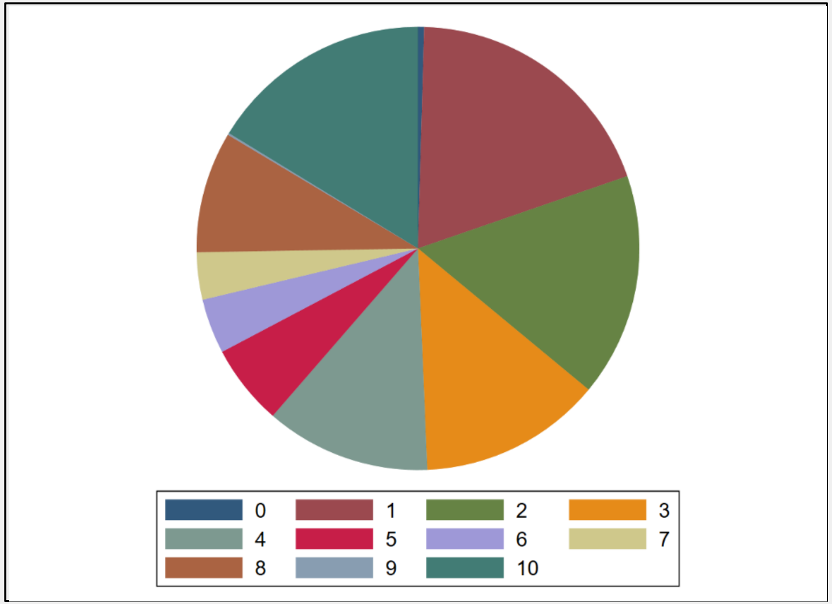
1 Minimum of 90 business days in reference period at beginning of activity of a participant
2 Adjustments for deviations to „neighbouring profiles“ (e.g. extreme to normal early payer, but still >30% in first hour)

DATA
Some descriptive statistics

Distribution of daily profiles



Distribution of dominant profiles

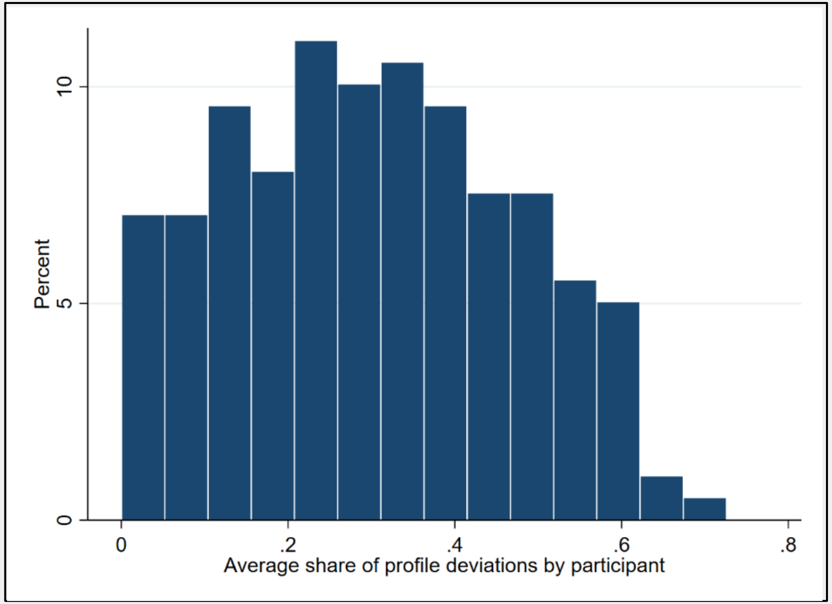


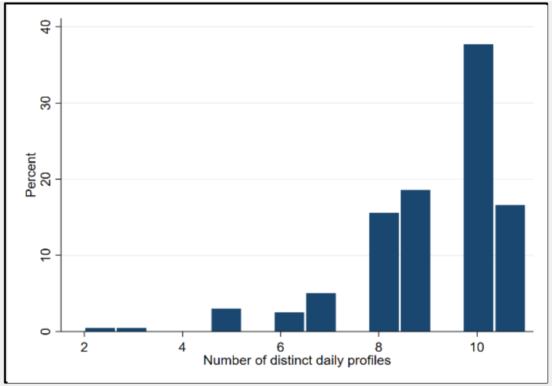
Legend

(0) No payment activity
(1) Early Birds
(2) Extreme Early Birds
(3) Second Wave
(4) Third Wave
(5) Long Sleepers
(6) Late Morning Payers
(7) Noon Payers
(8) Time-independent Payers
(9) Tea-time payers
(10) Late Payers

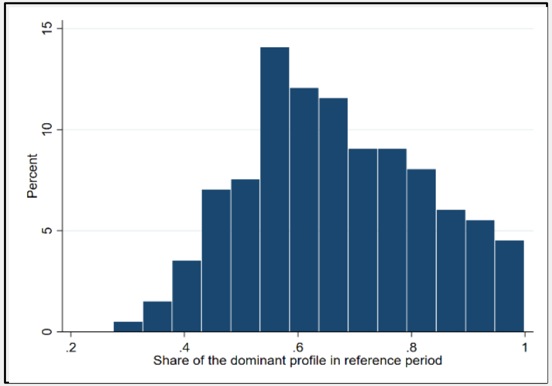
Data
Some descriptive statistics

Deviation share by participant





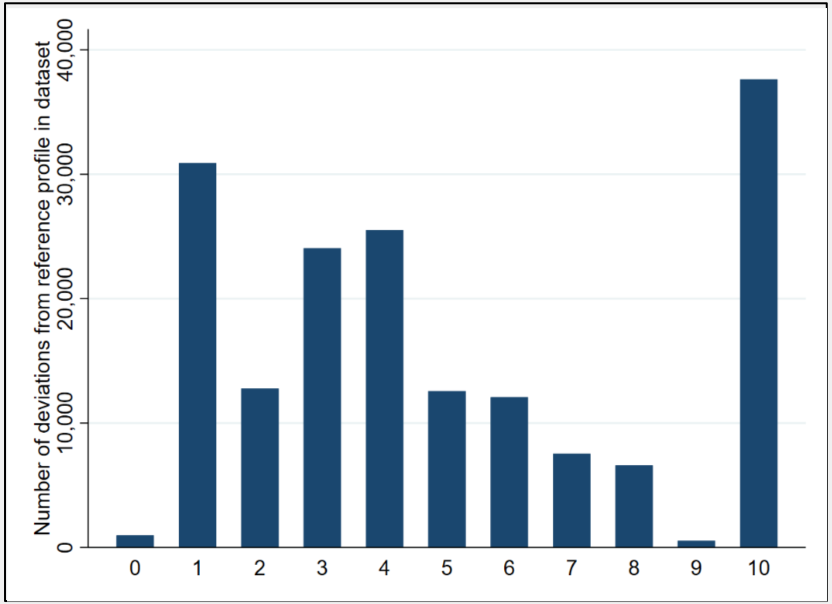
Number of distinct daily profiles per participant



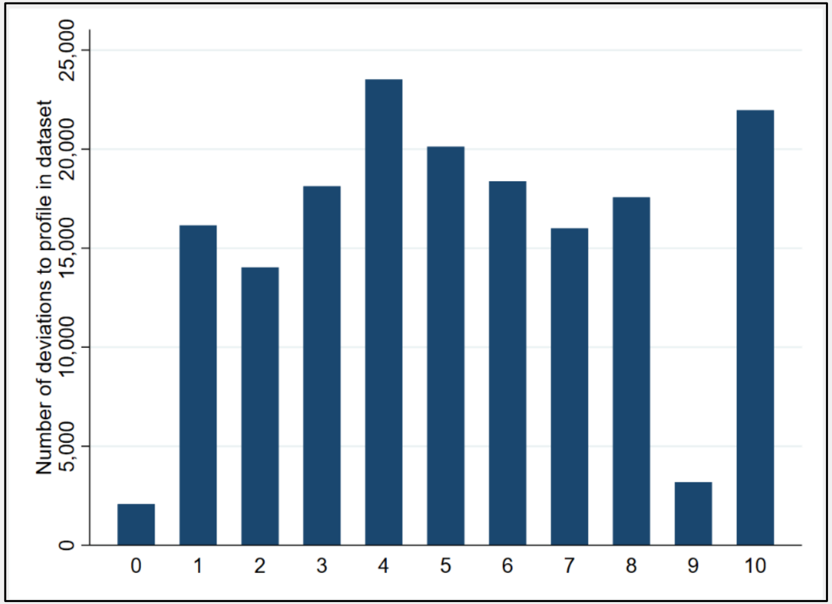
Share of the dominant profile in reference period

DATA
Some descriptive statistics

Deviations by reference profile



Deviations by deviating profile



Legend

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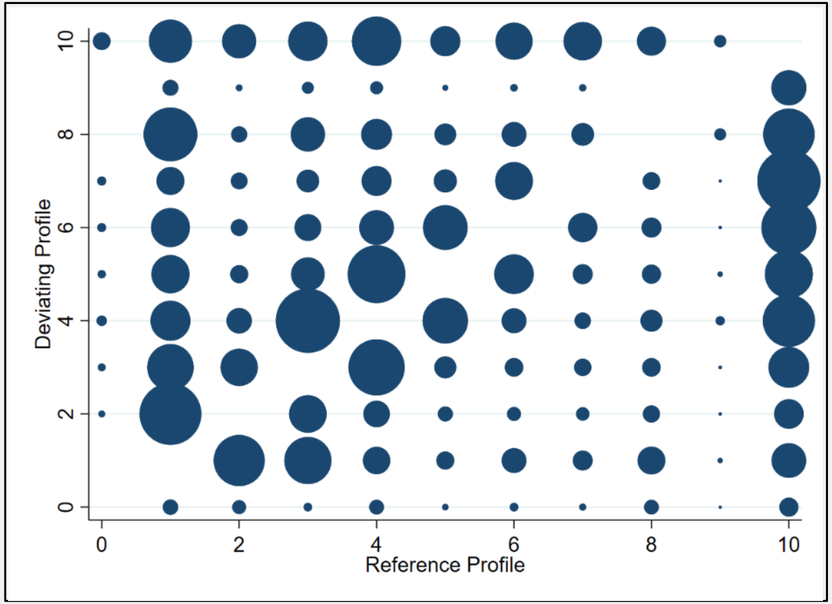
Deviations by reference and deviating profile



Note: Size of the markers proportional to number of deviations

Legend
(0) No payment activity
(1) Early Birds
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(10) Late Payers

Two steps of analysis

Profile Deviations

- Per participant and day
- Defined as: Profile is different than reference profile [0,1]

Explain Deviations

- Identify factors that correlate with daily deviations („explainable“)
- Quantify the magnitude of deviation („small“)

Predict pattern/profile

- Apply algorithm to predict an expected pattern/profile
- Compare predicted and actual pattern/profile

Relevant Profile Deviations

- Filter explained and predicted deviations
- (Filter small deviations)

Explain Deviations

Set of explanatory variables

- TARGET2 statistics (eg total value and volume for system and participant level, incoming and outgoing payment volumes and values)
- Seasonal and calendar variables (Weekdays, start and end of month, holidays, minimum reserve periods, years)
- Money market conditions
- (Could be extended further: Liquidity levels, stress indicators…)
- Explanatory variables are standardized to values between 0 and 1 using a Min-Max-Scaler

Method

Logistic regression with LASSO regularisation – predicting deviations

Heterogenous participants require estimation on participant level

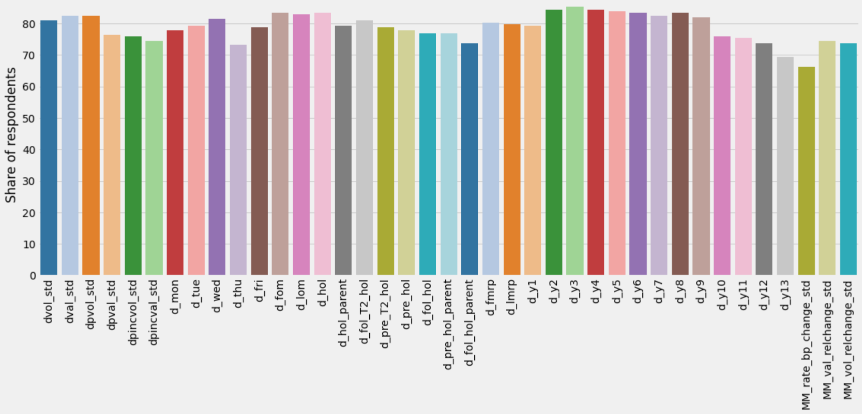
METHODOLOGY
Predict Pattern/Profile

Feed forward neural network as general artificial neural network approach

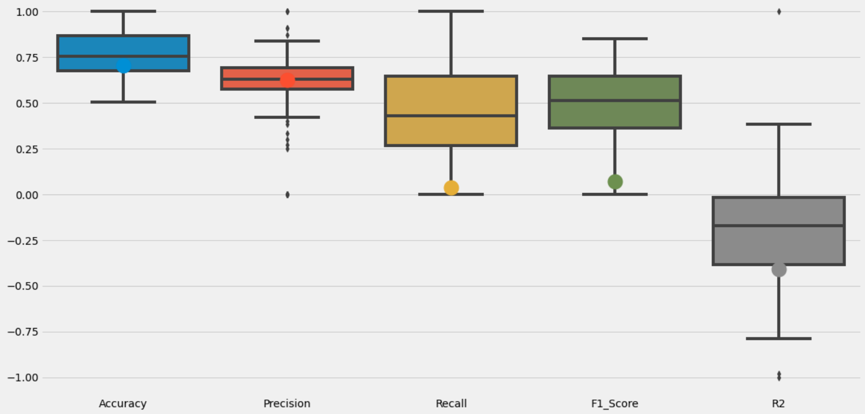
- The output is generated by using the same set of explanatory variables
- Rather intuitive and close to standard regression analysis
- Forecast
  - Deviation of profile from reference profile (similar to regression)
  - **Profile as multi-class**
  - Exact pattern (11 values)
- Set up on participant level

Results
Explain Deviations (Logistic Regression)

Coefficients

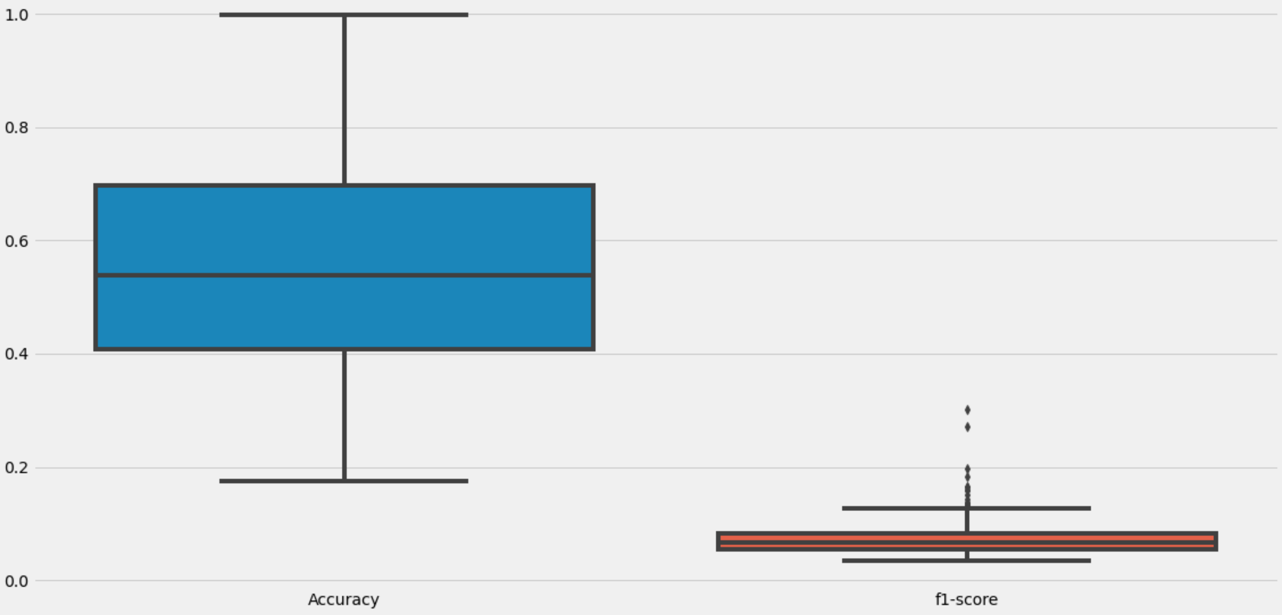


Model evaluation



Predict Profile (Feed Forward Neural Network)

Model evaluation



Identifying Deviations in Payment Behavior Using Participant Profiles
Conclusions, open questions and way forward

Conclusions:
- Predicting participant behaviour is challenging
- Heterogeneity plays an important role
- Results differ depending on metrics and parameters used
- Finding real outliers needs further reduction of number of deviations

Open questions
- How can we further improve model performance?
- How can we decide a model is good as we expect deviations?
- Can we distinguish “unpredictable” participants?

Way Forward:
- Analyse regression and FFNN on participant level to better understand impact of inputs
- Add additional explanatory variables
- Further refine FFNN (specification, weights), (explore alternative methods)
- Evaluate and select metrics to measure performance
- Cross check FFNN deviations and reference profile deviations
- Further reduce number of deviations, e.g. by distinguishing small deviations

Identifying Deviations in Payment Behavior Using Participant Profiles
Discussion and Questions

Thank you very much for your attention!

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