Analyzing retirement preparedness: a study of a Canadian investment data set

Yang Miao

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Western University

Objective

How to evaluate a person's financial wellness?

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$\hookrightarrow$ Will an investor have sufficient funds for their retirement?

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How to evaluate a person's financial wellness?

↪ Will an investor have sufficient funds for their retirement?

↪ How do different investment behaviours affect outcomes?

Data

A transaction-level investment data set provided by a registered investment dealer, including information on:

- **client**: demographic information, risk tolerance, accounts
- **position**: daily snapshot of the securities held in the account
- **transaction**: date, amount, category, etc.
- **financial security**: risk level, historical price

Summary of the data set

start date	2019-07-15
end date	2022-09-13
number of clients	56,288
number of accounts	115,326
number of securities	31,896

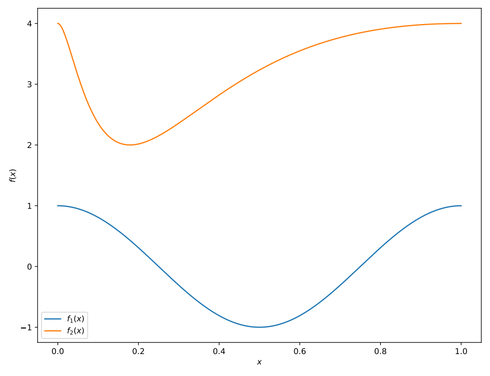
account type	count	percentage
Registered Retirement Savings Plan (RRSP)	27,404	23.76
Tax-Free Savings Account (TFSA)	26,767	23.21
Cash	18,436	15.99
Retirement Income Fund (RIF)	9,145	7.93
Locked-in retirement account (LIRA)	8,241	7.15
Registered Education Savings Plan (RESP)	6,585	5.71
Spousal RRSP	5,941	5.15
Life Income Fund (LIF)	3,395	2.94
Spousal RIF	2,072	1.80
Others	7,340	6.36

Canadian RRSP

- income earned in the RRSP is usually exempt from tax
- payments from the plan is taxed
- annual contribution limit
- at maturity (71 years old): transfer to a registered retirement income fund (RRIF), convert to a life annuity, or receive commutation payments

Dynamic time warping: example

$$f_1(x) = \cos(2\pi x), \quad f_2(x) = \cos\left(2\pi d(x)\right)$$
$$d(x) = \frac{\ln(20x+1)}{\ln 21}$$



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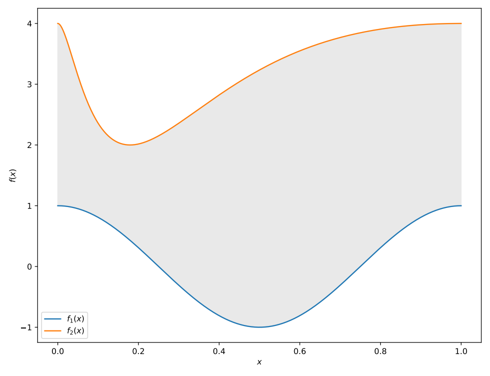

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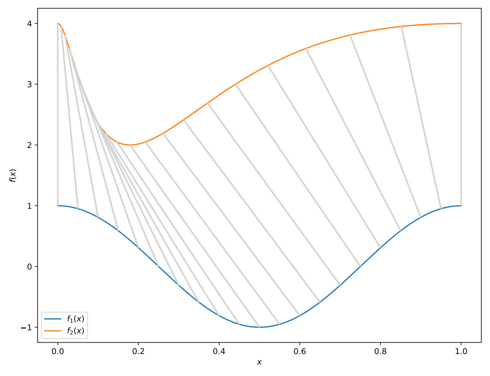
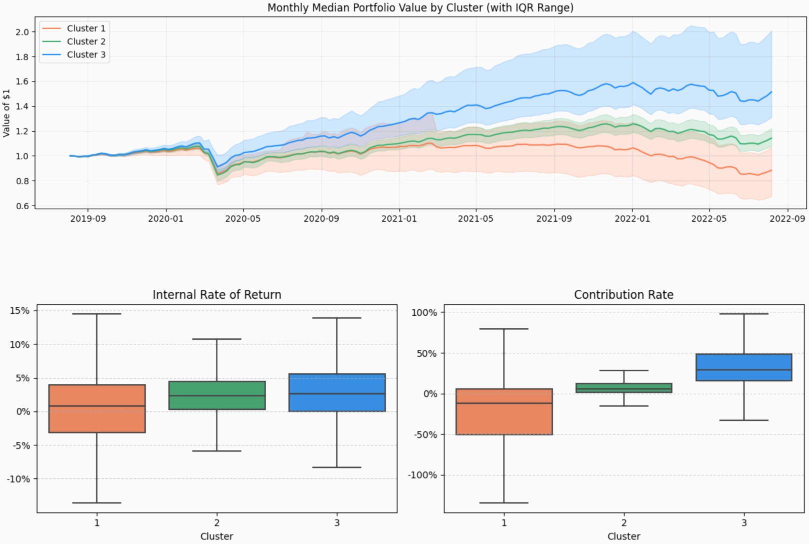




Monthly Median Portfolio Value by Cluster (with IQR Range)
Cluster 1
Cluster 2
Cluster 3
Value of $1
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0.6
2019-09
2020-01
2020-05
2020-09
2021-01
2021-05
2021-09
2022-01
2022-05
2022-09
Internal Rate of Return
15%
10%
5%
0%
-5%
-10%
1
2
3
Cluster
Contribution Rate
100%
50%
0%
-50%
-100%
1
2
3
Cluster

Simulation: A model for security price

We need a model that mimics the financial market, especially

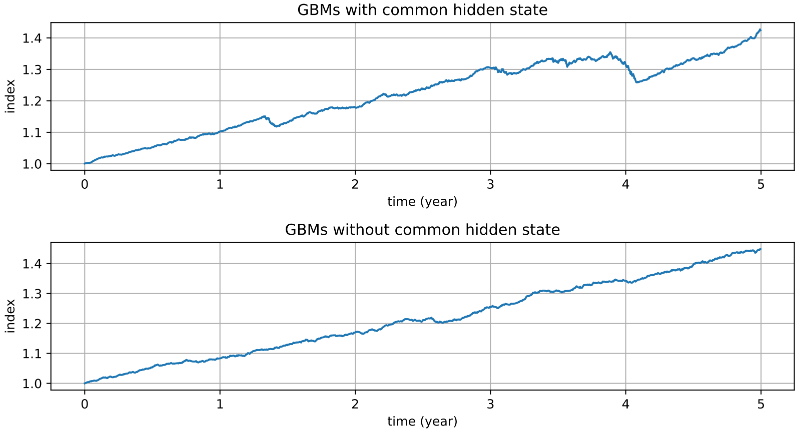
- Periods of high volatility and periods of low volatility
- Sudden market drops, i.e., market crashes
- Dependency among securities

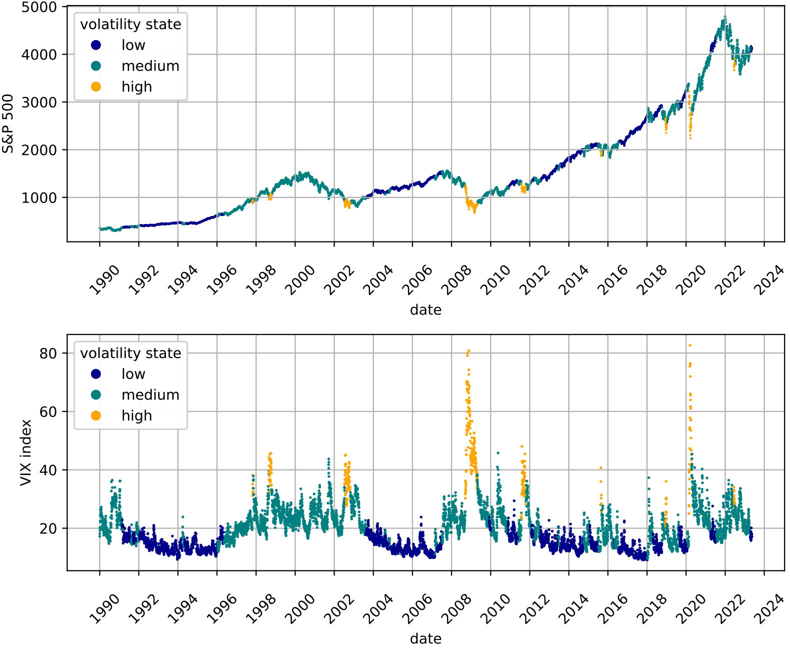
Regime switching model with common hidden state

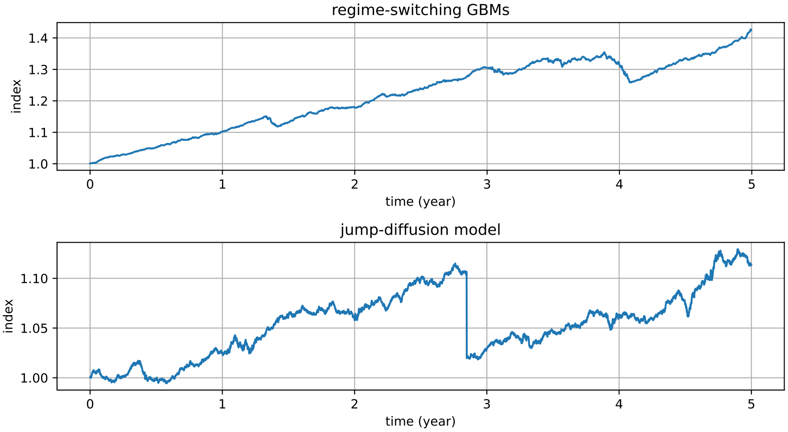
Let Z_t be a continuous-time Markov chain with m states that represent the volatility state of the financial market at time t. Suppose there are N securities available to the investors. Given the volatility state Z_t, the value of the kth security, $X_{k,t}$, follows

$$\mathrm{d}X_{k,t} = \mu_k(Z_t)X_{k,t}\mathrm{d}t + \sigma_k(Z_t)X_{k,t}\mathrm{d}W_{k,t}, \quad k = 1, 2, \cdots, N,$$

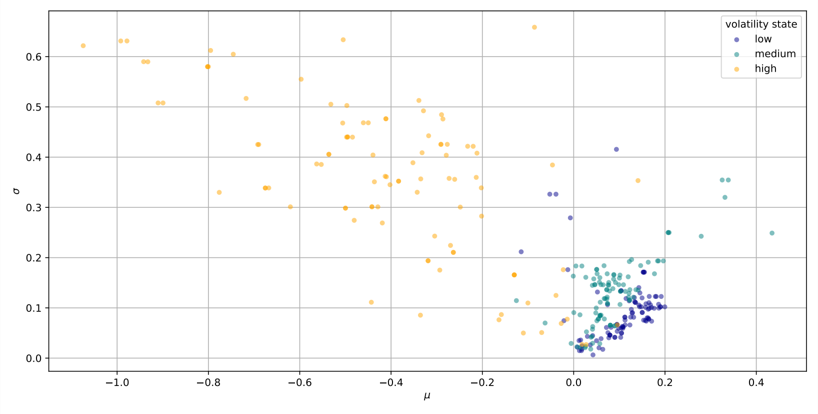
where $\mu_k : \{1, 2, \cdots, m\} \to \mathbb{R}$ and $\sigma_k : \{1, 2, \cdots, m\} \to \mathbb{R}$ are two functions that represent the drift and the volatility of the kth security, and $W_{k,t}$'s are independent Brownian motions.


GBMs with common hidden state
index
1.0
1.1
1.2
1.3
1.4
0
1
2
3
4
5
time (year)
GBMs without common hidden state
index
1.0
1.1
1.2
1.3
1.4
0
1
2
3
4
5
time (year)


volatility state
low
medium
high
S&P 500
date
VIX index
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018
2020
2022
2024



regime-switching GBMs
index
1.4
1.3
1.2
1.1
1.0
0
1
2
3
4
5
time (year)
jump-diffusion model
index
1.10
1.05
1.00
0
1
2
3
4
5
time (year)


volatility state
low
medium
high
0.6
0.5
0.4
0.3
0.2
0.1
0.0
σ
−1.0
−0.8
−0.6
−0.4
−0.2
0.0
0.2
0.4
μ

Simulation: A summarization of trading behaviours

Category	Description
Recency	Number of days since last trade on record
Frequency	Total number of trades
	Average number of days between trades
Monetary	Buy and sell size totals
	Buy and selle size minimum and maximum
	Trade size by type
	Variability of trade size by type
Profile	Demographic information

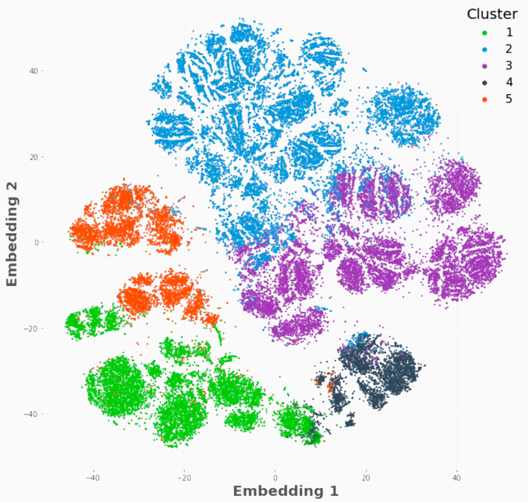


Figure 1: Visualization of the clusters using t-SNE, Thompson et al. (2021)

Clusters	KYC	Trade Behaviour
Active Traders	Average age, income and demographics.	Trade frequently in large amounts and appear sensitive to market influences.
Early Savers	Slightly younger but average income and demographics.	Smaller, regular deposits making use of preauthorized contributions.
Just-in-Time	Average age, income and demographics.	Infrequent trades at seemingly random intervals.
Older Investors	Older but average, income and demographics. Average investment knowledge.	Primarily withdrawals, dividends, and interest payments.
Systematic Savers	Average age, income and demographics.	Larger, systematic trades and re-balancing.

Table 1: Summary of clustering results, Thompson et al. (2021)

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Rebalancing

Type	When	How
Reactive (A)	the return of one asset in the portfolio is in the bottom 5% percentile among the securities with the same risk rating	sell the current security, buy the best performing alternative
Systematic (B)	rebalance once a year	choose the best performing security within each risk rating
Inactive (C)	Never	N/A

Reactions to market crashes

Type	How
Panicking (1)	Sell everything and keep the cash. Re-enter the market when the index returns to pre-crash level
Adjusting (2)	Decrease the portfolio risk moderately
Indifferent (3)	Do nothing

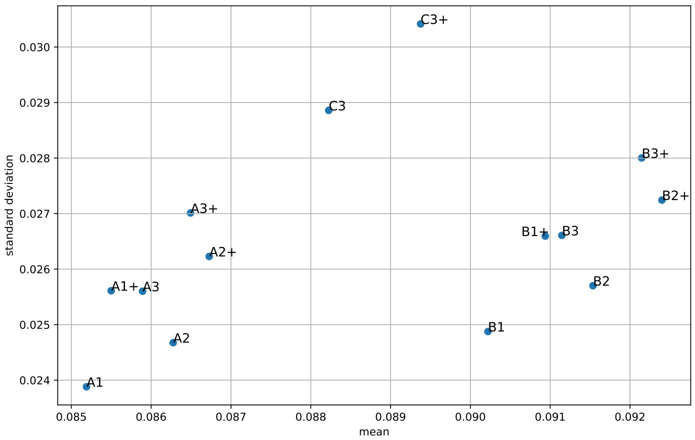
Savings

Type	How
Systematic (+)	Contribute a fixed amount monthly
Never	Never make additional contributions

Combinations of behaviours

	Reactive (A)	Systematic (B)	Inactive (C)
Panic (1)	A1, A1+	B1, B1+	
Adjusting (2)	A2, A2+	B2, B2+	
Indifferent (3)	A3, A3+	B3, B3+	C3, C3+

Simulation results



Rebalancing: A: Reactive B: Systematic C: Inactive
Reactions: 1: Panicking 2: Adjusting 3: Indifferent
Savings: +: Systematic

Conclusions

- Observations confirmed by both the machine learning methods and the simulation study.
- We discover that...
    - Panic selling could be detrimental to investment.
    - It is difficult to beat the market by adopting a more active trading strategy.
    - Consistent savings is important for achieving better investment outcome.
- We may provide general advices to investors based on these findings.
- Future work: combination with portfolio optimization, providing clients with customized advices based on their needs, etc.

References

J. R. Thompson, L. Feng, R. M. Reesor, and C. Grace. Know your clients' behaviours: a cluster analysis of financial transactions. *Journal of Risk and Financial Management*, 14(2):50, 2021.