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The Tranching Dilemma

A Cost-Aware Approach to Mitigate Rebalance Timing Luck in Factor Portfolios

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Abstract

Rebalance Timing Luck (RTL) refers to the performance dispersion that arises between otherwise identical strategies differing only in their rebalancing dates. Although often overlooked, RTL can reach substantial magnitudes in high-turnover strategies, and compounding effects may amplify its long-term impact. Portfolio tranching is a well-established method to mitigate RTL exposure, yet its real benefit is likely to depend on the investor's assets under management (AUM). In this paper we empirically examine RTL in a U.S. equity momentum portfolio rebalanced monthly. Between 1991 and 2024, the gap in compound annual growth rate (CAGR) between the most and least favorable rebalancing schedules reached almost 350 basis points. We then develop a framework to determine the optimal degree of tranching under realistic assumptions about transaction costs. Results show that while tranching consistently reduces RTL, its net advantage is primarily confined to highly capitalized investors or those involved in the design of factor-based investment vehicles, whereas for smaller investors the additional trading costs often outweigh the benefits. Retail investors must therefore accept being exposed to RTL risk as an inherent and largely unavoidable aspect of rotation-based investing.

Keywords: Rebalance Timing Luck, Portfolio Construction, Momentum Factor, Quantitative Momentum, Factor Investing

1 Introduction

In the context of constructing and managing investment portfolios, the term rebalance timing luck (RTL) describes the *"potential performance dispersion between two identically managed strategies with different rebalance schedules"* (Hoffstein et al., 2020).

Although the rebalancing policy of an investment strategy may seem superficial or inconsequential at first glance, research beginning with Blitz et al. (2010) has shown otherwise. Several academics have since quantified the impact of rebalance timing luck in factor portfolios (also known as smart beta portfolios), concluding that its effects are material and cannot be overlooked.

For instance, Hoffstein et al. (2020) build long-only indices that replicate exposure to well-known U.S. equity factors (size, value, momentum, low volatility and quality) and change their rebalance calendars to measure rebalance timing luck. They find that RTL effects are meaningful, frequently surpassing 100 basis points annualized, and highly sensitive to the *"frequency of rebalancing, portfolio concentration, and the nature of the underlying strategy"*. Their results indicate that RTL is effectively an *"uncompensated source of risk"*, complicating evaluation of strategies, peer groups, and their benchmarking.

Building on the existing literature, this study pursues a dual objective. First, using a concentrated momentum strategy as a case study, it seeks to empirically demonstrate the magnitude and implications of rebalance timing luck (RTL). Second, it aims to introduce a framework that practitioners can employ to determine the optimal degree of tranching to implement within their factor-based portfolios.

2 Base Strategy and Methodology

The rotational momentum strategy considered in our case study is inspired by the methodology presented in the book *Quantitative Momentum* (Gray and Vogel, 2016). Stock selection follows these steps:

1. **Liquidity filter:** From the Russell 3000 universe (including historical constituents), we first select the 1000 most liquid stocks.[1]

2. **Momentum screen:** Within this subset, we identify the top 100 stocks ranked by their past yearly return, calculated ignoring the most recent month (*2–12 MOM*).[2]

3. **Momentum quality selection:** From these candidates, the 20 stocks with the highest momentum quality are selected, following the framework of Da et al. (2014). The authors measure momentum quality using an information discreteness (ID) proxy, which captures whether past cumulative returns were generated by many small daily gains or a few large jumps. Formally, ID is defined as

$$ID = \text{sgn}(\mathit{2\text{–}12\ MOM}) \times [\%neg - \%pos] \tag{1}$$

   where $\%pos$ and $\%neg$ represent the percentage of days with positive and negative returns during the formation period, respectively; $\text{sgn}(\mathit{2\text{–}12\ MOM})$ equals $+1$ if $\mathit{2\text{–}12\ MOM} > 0$ and -1 otherwise. A lower ID value indicates higher momentum quality.

At each predetermined rebalancing date, the strategy invests in the 20 selected stocks, assigning an equal weight of 5% to each position: holdings remain unchanged until the next rebalancing date, as no interim adjustments are allowed.

The dataset used for the simulations is sourced from Norgate Data, covering the period from 1991 to 2024. All prices are adjusted for stock splits, corporate actions, and dividends. The dataset also includes historical index constituents, thereby eliminating

[1] We measure liquidity as the rolling 252-day median dollar volume of a stock.

[2] This measure of momentum is consistent with the academic definition of momentum introduced by Jegadeesh and Titman (1993).

survivorship bias. The risk-free rate applied to both positive and negative cash balances is obtained from Kenneth French's data library.[3] Moreover, the backtesting framework is based on the following assumptions:

- All signals, and consequently the amount of shares to buy or sell, are computed at the close of day t and executed at the close of day $t+1$.
- In the event of a delisting, the notional value is transferred to the cash balance without being logged as a transaction or having impact on turnover.[4]
- Shares are assumed to be bought and sold at their historically adjusted prices, thereby automatically incorporating dividend reinvestment into the time series.
- Trading of fractional shares is allowed.

Finally, it is important to emphasize that the objective of this paper is not to propose a ready-to-trade investment strategy, but rather to present a realistic case study illustrating how the effects of rebalance timing luck can be analyzed and potentially addressed.

[3] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[4] The portfolio is structured to hold fewer than 20 positions only in the event of a delisting, when a stock becomes non-tradable. In such cases, the portfolio retains a residual cash balance, which accrues interest at the prevailing risk-free rate. Conversely, if the cash position turns negative, it is assumed to incur a financing cost equal to the risk-free rate. For example, consider an equal-weighted portfolio of 20 stocks: if 19 positions appreciate while one underperforms and is replaced at the next rebalancing date, the new position is assigned a 5% weight relative to the current net liquidation value (NLV). However, the proceeds from selling the underperforming stock may be insufficient to fund this allocation, as the overall portfolio value has increased due to gains in the other 19 holdings: this shortfall results in a small negative cash balance, which incurs financing costs. A similar effect may occur when portfolio weights are calculated using today's NLV but trades are executed at the following day's close. If prices rise in the interim, the required allocations may exceed the available capital, again resulting in a temporary negative cash balance.

3 Standard Monthly Rebalancing

We define 20 variations of the same monthly rebalancing schedule. The first variation rebalances at the close of the first trading day of every month (using signals from the last day of the previous month), the second at the close of the second trading day, and so on, up to the twentieth trading day. In months with fewer than n trading days, where n denotes the specific trading day chosen for rebalancing, the last available trading day is used. This adjustment ensures that each month has exactly one rebalancing event, maintaining consistency across all months and avoiding gaps.

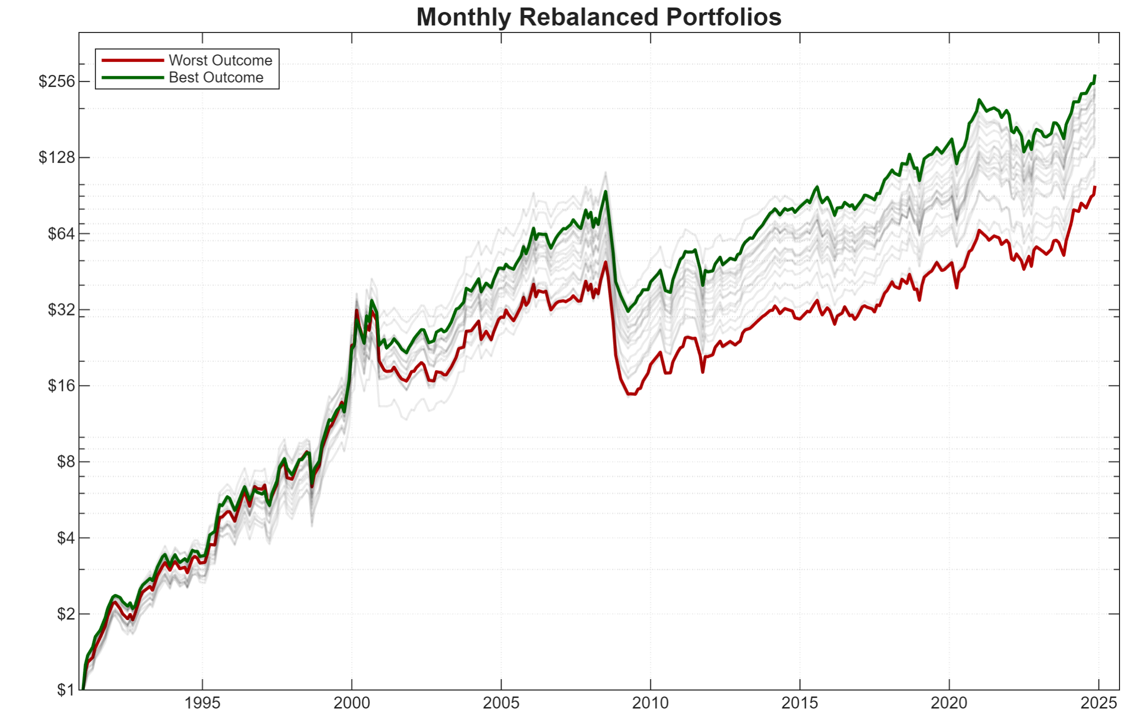

Figure 1: Growth of $1 for 20 variations of the same momentum strategy applied to historical constituents of the Russell 3000 Index. Each simulation differs only in the trading day of the month chosen for rebalancing. The best-performing and worst-performing versions of the strategy are highlighted in bold.

	Rebal Frequency	Trading Day	CAGR (%)	Max Drawdown (%)	Sharpe (Rf 0%)	Sharpe (Rf 2.45%)	Avg Trades / Year	Annual Turnover (%)	Beta	Alpha (%)	Alpha pVal
🔴	M	0	14.53	-74.70	0.61	0.53	339.97	1065.01	1.25	3.07	0.334
	M	1	16.37	-69.31	0.67	0.58	339.97	1063.60	1.25	4.66	0.140
	M	2	16.60	-69.84	0.67	0.59	339.64	1059.26	1.25	4.80	0.126
	M	3	16.10	-69.52	0.66	0.57	339.49	1060.69	1.25	4.38	0.163
	M	4	16.91	-70.60	0.68	0.60	339.29	1058.25	1.25	5.09	0.106
	M	5	17.83	-71.69	0.71	0.63	339.44	1058.39	1.24	5.90	0.060
	M	6	18.01	-72.24	0.72	0.63	340.26	1067.33	1.24	6.09	0.051
	M	7	17.09	-73.61	0.69	0.60	338.52	1051.81	1.25	5.23	0.093
	M	8	17.09	-74.34	0.69	0.60	340.20	1065.99	1.25	5.26	0.095
🟢	M	9	18.01	-71.20	0.72	0.63	339.85	1062.72	1.25	6.05	0.054
	M	10	17.40	-74.48	0.70	0.61	339.11	1055.16	1.26	5.46	0.080
	M	11	17.63	-70.73	0.71	0.62	339.35	1058.11	1.25	5.70	0.068
	M	12	16.02	-71.25	0.66	0.57	338.90	1053.72	1.25	4.33	0.165
	M	13	15.30	-73.55	0.63	0.55	339.35	1058.81	1.26	3.65	0.245
	M	14	15.42	-73.35	0.64	0.55	338.87	1053.00	1.26	3.78	0.232
	M	15	16.66	-71.84	0.67	0.59	339.67	1061.25	1.26	4.85	0.124
	M	16	17.38	-73.40	0.70	0.61	340.56	1069.84	1.25	5.49	0.081
	M	17	17.55	-72.12	0.70	0.62	340.73	1072.44	1.24	5.73	0.071
	M	18	17.58	-73.27	0.70	0.62	339.44	1058.12	1.25	5.70	0.072
	M	19	15.08	-74.85	0.63	0.54	338.96	1054.79	1.25	3.51	0.266

Table 1: Key statistics for 20 variations of the same monthly-rebalanced momentum strategy. The analysis period spans from January 2, 1991, to November 15, 2024. Trading day 0 refers to the first trading day of the month, while trading day 19 corresponds to the 20th trading day (these days may be subject to the adjustment procedure outlined at the beginning of Section 3). The best- and worst- performing simulations are marked with green and red dots, respectively. Results incorporate interest paid or received and assume no transaction costs. Alpha and Beta values are obtained by regressing the strategy's excess returns on the market excess return (Mkt-RF), as provided by Kenneth French's data library.

Our tests reveal a pronounced effect of rebalance timing luck (RTL), with the difference in CAGR between the most and least favorable rebalancing dates amounting to 348 basis points. Given that this dispersion effectively compounds over time, we can see how in the least favorable run an initial investment of $1 grows to $99, whereas in the most favorable run it grows to $272, a difference of almost threefold.

This illustrates how a seemingly innocent decision (the choice of rebalancing date in a rotational stock selection strategy) can result in massive divergences in realized wealth over extended time horizons.

All simulations exhibit positive alphas, with only two reaching marginal significance at the 5% level.[5] Trading activity remains elevated, with annual turnover around 1,060% and roughly 340 executed trades per year. Since no rebalancing threshold is imposed to restrict minor position adjustments, this figure also includes micro-rebalancing trades that, in a real-world setting, a portfolio manager might decide to skip. In this study, we deliberately omit such a constraint to ensure that rebalance timing luck (RTL) is not affected by anything beyond the variation in rebalancing days.

[5] Proprietary research shows that the strategy can be adjusted to achieve statistically significant alphas in a more consistent way.

4 Portfolio Tranching

Portfolio tranching is a well-established methodology that has been proven effective in mitigating rebalance timing luck (RTL) by both Blitz et al. (2010) and Hoffstein et al. (2019). It revolves around the idea of splitting a portfolio into N sub-portfolios (i.e., tranches), each traded independently and on different rebalancing schedules. In this way, the impact of any single rebalance is reduced, and with it also the likelihood of being exceptionally lucky or unlucky.

The authors also demonstrate that relative performance between different rebalance dates is nonstationary. As Hoffstein et al. (2019) note, *"performance deviations due to rebalance timing luck are not expected to mean-revert and are therefore expected to be random but permanent artifacts"*. Consequently, one effective way to mitigate rebalance timing luck is to evenly distribute risk across multiple tranches, each rebalanced on staggered schedules.

To quantify the effects of tranching on our concentrated momentum portfolio, we first define the tranching schedules to be tested. Assuming that a month contains approximately 20 trading days, and that tranches within each schedule are evenly spaced from one another, the possible tranching schedules can be defined as follows:

Tranches	Possible Schedules	
1	20	[0], [1], . . . , [19]
2	10	[0, 10], [1, 11], . . . , [9, 19]
4	5	[0, 5, 10, 15], . . . , [4, 9, 14, 19]
5	4	[0, 4, 8, 12, 16], . . . , [3, 7, 11, 15, 19]
10	2	[0, 2, . . . , 16, 18], [1, 3, . . . , 17, 19]
20	1	[0, 1, 2, . . . , 19]

Table 2: Tranching schedules for a 20-day trading month. Each bracket represents a specific tranching schedule, and the numbers within each bracket indicate the trading days of the month on which tranches are rebalanced, with each number corresponding to a different tranche. Tranches within each schedule are always kept at evenly spaced intervals.

For example, the 1-tranche configuration corresponds to the base case outlined in Section 3, where performance dispersion arises from the possibility of choosing across 20 different rebalancing schedules. If the portfolio is instead split into 5 tranches, there are 4 possible tranching schedules that maintain interventions evenly spaced. In the first schedule, rebalancing occurs on trading days [0, 4, 8, 12, 16], with each day corresponding to a specific tranche being rebalanced. The second schedule trades on days [1, 5, 9, 13, 17], the third on [2, 6, 10, 14, 18], and the fourth on [3, 7, 11, 15, 19]. Conversely, if the portfolio is divided into 20 tranches, only one schedule is possible: portfolio interventions occur every day, with each day corresponding to the rebalancing of a different tranche.[6]

We then run tests across all possible tranching schedules (42 in total) and compute the mean portfolio statistics corresponding to each of the six tranching configurations considered (1, 2, 4, 5, 10, and 20 tranches). We measure RTL as the difference in CAGR between the best- and worst-performing portfolios within each tranching configuration, evaluated at the end of our long-term simulations. This allows us to assess how, on average, performance, trading activity, and rebalance timing luck evolve as the number of tranches increases.

Number of Tranches	**Mean CAGR (%)**	**RTL (%)**	**Sharpe Ratio (Rf 2.45%)**	**Average Trades / Year**	**Annual Turnover (%)**
1	16.73	3.48	0.59	339.58	1060.41
2	16.81	2.05	0.60	679.16	1060.38
4	16.84	1.01	0.60	1357.48	1059.98
5	16.84	0.63	0.60	1696.48	1059.80
10	16.84	0.07	0.60	3391.53	1059.49
20	16.83	0.00	0.60	6748.10	1056.20

Table 3: Aggregate performance statistics of the monthly-rebalanced momentum strategy for different numbers of tranches. Values represent the mean of key metrics (CAGR, Sharpe ratio, average trades per year, and annual turnover) across all possible tranching schedules. The analysis period spans from January 2, 1991, to November 15, 2024. Trading days are adjusted according to the procedure described in Section 3.

We observe that increasing the number of tranches does not materially affect the mean CAGR, while rebalance timing luck (RTL) is consistently reduced. This confirms that tranching is not intended to enhance performance but rather to reduce the potential dispersion around a portfolio's expected return. As also documented by Blitz et al. (2010), annual turnover remains virtually unchanged. We find that the number of trades per year scales linearly with the number of tranches (e.g., with five tranches, the average number

[6] Trading days are always subject to the adjustment procedure outlined in Section 3.

of trades is roughly five times that of a single-tranche portfolio).

These outcomes are consistent with expectations: since tranching effectively creates N independent sub-portfolios, the total number of trades increases proportionally with N. However, because each tranche holds a smaller fraction of the overall portfolio, the size of each individual trade decreases accordingly. As a result, while trading activity becomes more frequent, the total traded notional (and therefore overall turnover) remains unchanged. Formally, this relationship is reflected in the position sizing formula for an equal-weighted portfolio under a tranched approach, where the weight of each position is $1/(M \times N)$, with M denoting the maximum number of holdings per tranche (20 in our case) and N the number of tranches into which the portfolio is divided.

Figure 2 illustrates how rebalance timing luck (RTL) and the number of trades scale with the number of tranches. An interesting observation is that our results seem to confirm the findings of Hoffstein et al. (2019), who conclude that tranching reduces RTL by a factor of $1/N$.

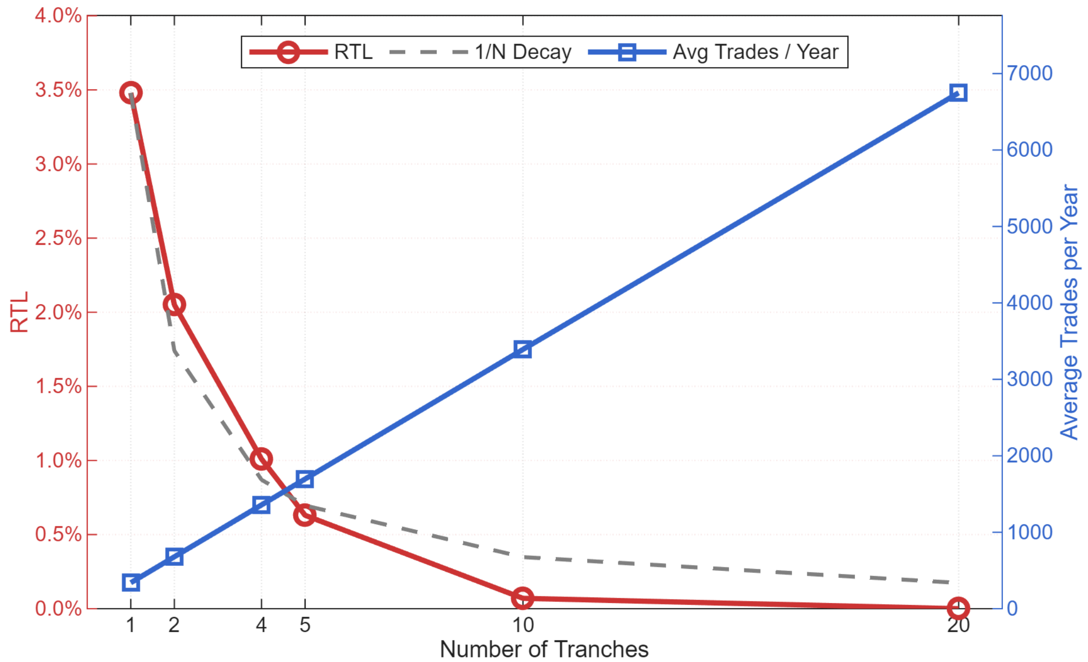

Figure 2: Relationship between the number of tranches, rebalance timing luck (RTL, red line), and average number of trades per year (blue line). The dotted grey line represents the decay proportional to $1/N$, as suggested by Hoffstein et al. (2019).

While it is clear that increasing the number of tranches consistently reduces rebalance timing luck (RTL), it also leads to higher trading activity. This raises the question of whether, once realistic transaction cost estimates (including both fees and market impact) are considered, investors with different levels of assets under management (AUM) might experience varying benefits from tranching. In other words, we seek to determine whether an optimal degree of tranching exists, or if increasing the number of tranches always leads to more favorable outcomes.

To investigate this, we move from analyzing gross-of-fee portfolios to net-of-fee portfolios, incorporating realistic cost assumptions. For each configuration consisting of N tranches, we evaluate the following objective function:

$$U(N) = \text{CAGR}(N) - \text{RTL}(N) \tag{2}$$

where CAGR(N) represents the average long-term compound annual growth rate obtained across all tranching schedules using N tranches, and RTL(N) measures the dispersion in outcomes, defined as the difference in CAGR between the best- and worst-performing schedules over the full backtest period.

For transaction costs, we assume the standard Interactive Brokers tier of \$0.0035 per share, with a minimum commission of \$0.35 per trade (these values are doubled for sell transactions to account for SEC clearing fees). Market impact is estimated using the I-Star model, with parameter values calibrated by Kissell (2020) for the overall U.S. equity market, namely: $a_1 = 708$, $a_2 = 0.55$, and $a_3 = 0.71$. One important adjustment implemented in our backtest concerns the normalization of transaction costs. Since our objective is to evaluate the impact of transaction costs for specific AUM levels, and given that the strategy's AUM evolves over time as profits accumulate, a normalization procedure is required. Specifically, transaction costs are always computed relative to a fixed reference AUM, and then rescaled so that their impact on the current AUM is equivalent to what it would be under the reference AUM. This ensures that the effect of transaction costs remains consistent and comparable across time, independent of portfolio growth.

The normalization procedure can be formalized as follows:

$$\text{tcosts}_t^{\text{norm}} = \text{AUM}_{t-1} \times \frac{\text{tcosts}_t(\text{AUM}_{\text{ref}})}{\text{AUM}_{\text{ref}}} \quad (3)$$

- $\text{tcosts}_t^{\text{norm}}$ is the normalized transaction cost at time t, applied to the actual AUM.
- AUM_{t-1} represents the actual assets under management held by the strategy at time $t-1$.
- AUM_{ref} denotes the fixed reference AUM used for normalization purposes.
- $\text{tcosts}_t(\text{AUM}_{\text{ref}})$ indicates the total transaction costs (including both fees and market impact) computed as if the trades were executed using the reference AUM level.

We evaluate our objective function for five different reference AUMs ($25K, $100K, $1M, $10M, and $100M), covering a range from retail-sized to institutional-sized portfolios, and results are shown in Figure 3.

The plots clearly indicate that for retail-sized portfolios ($25K), the greatest benefit is achieved with 2 tranches. Beyond this level, the performance decay due to transaction costs begins to offset the benefits of reduced rebalance timing luck. This occurs because tranching involves a higher number of smaller-sized trades, which disproportionately impacts retail investors who frequently encounter minimum commission thresholds. These findings are consistent with Zarattini et al. (2025), who show that trend-following strategies on a broad stock universe are heavily affected by transaction costs for smaller AUMs. Conversely, as AUM increases, tranching becomes progressively more advantageous. For a better-capitalized retail investor replicating our concentrated momentum portfolio with approximately $100K in capital, the optimal number of tranches is 5, with diminishing benefits thereafter. In contrast, for institutional investors (represented by reference AUM levels from $1M to $100M), the benefits of applying tranching to our strategy increase monotonically.

This is explained by the fact that smaller trades mitigate market impact, which is a primary concern for larger portfolios and institutional investors. This effect is rather pronounced for the largest reference AUM ($100M), where the utility function is negative

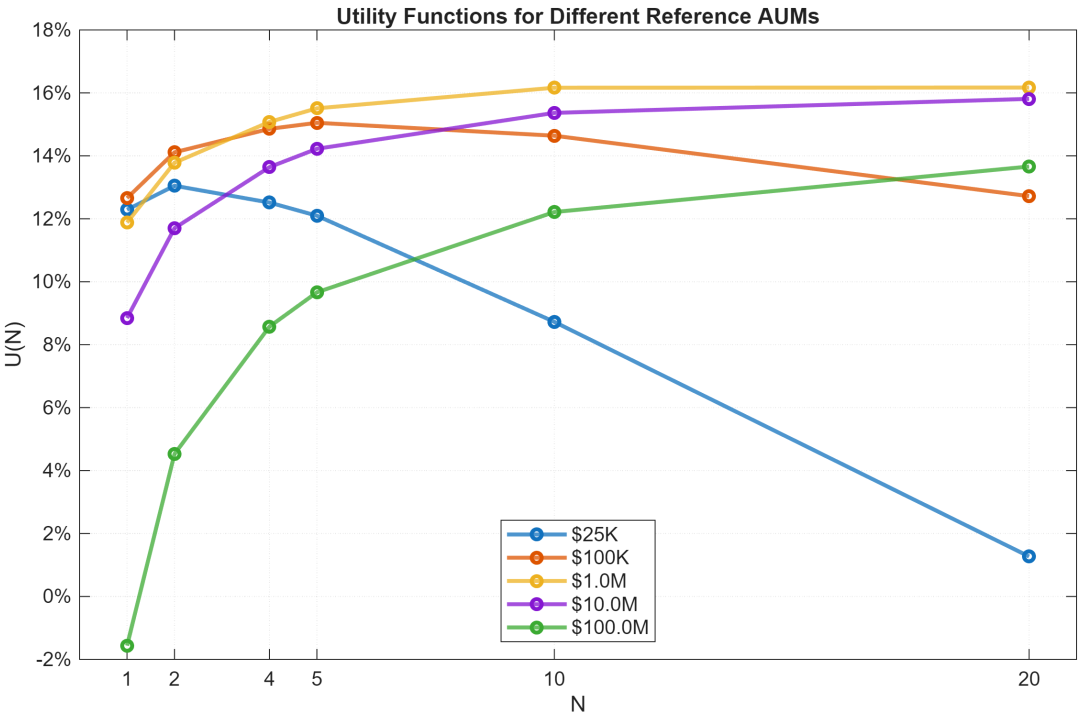

Figure 3: Utility functions for different reference AUM levels, illustrating how the benefits of tranching vary across portfolio sizes. Lines correspond to the utility functions evaluated at each reference AUM: blue ($25K), orange ($100K), yellow ($1M), purple ($10M), and green ($100M). Each utility function is defined as $U(N) = \text{CAGR}(N) - \text{RTL}(N)$, where $\text{CAGR}(N)$ represents the average CAGR obtained across all tranching schedules using N tranches, and $\text{RTL}(N)$ measures rebalance timing luck across said schedules.

for a single-tranche approach, implying that the expected net-of-fee CAGR is lower than the performance dispersion caused by RTL. While our execution assumptions may not reflect actual institutional practices (such as splitting trades across multiple sessions), this framework serves as a useful proxy to illustrate the principle that larger portfolios are severely harmed by "chunky" rebalancing practices. One additional point is that these utility functions are strictly specific to our strategy. For example, if the number of holdings in the momentum portfolio were increased, the performance decay of the $25K AUM portfolio would be even more pronounced, as the strategy would generate more trades. Similarly, if we were to consider a low-volatility portfolio with modest turnover, the utility functions would be more strongly influenced by trading costs rather than rebalance timing luck. That said, we believe the real added value of our approach lies not in the specific results presented here, but in the idea that this framework can help individual investors and portfolio managers determine the optimal degree of tranching, given their specific factor exposures and AUM characteristics.

5 Conclusion

Building upon the existing literature, this study confirms that rebalance timing luck can be a highly impactful source of performance dispersion, with meaningful implications for realized wealth over time. In the context of the concentrated momentum strategy analyzed in our tests, the effects of rebalance timing luck (RTL) can be documented at intra-month resolution, with dispersion reaching almost 350 basis points in compound annual growth rate (CAGR).

After introducing the principles behind portfolio tranching, our tests confirm some key findings from prior literature, in particular Blitz et al. (2010), who show that turnover does not increase with tranching, and Hoffstein et al. (2019), who report a decay factor of $1/N$ for the reduction in RTL when splitting a portfolio in N overlapping sub-portfolios.

In investigating whether an optimal degree of tranching exists, we propose a framework based on optimizing a utility function that combines CAGR and RTL, evaluated on net-of-fee portfolios. The results clearly show that the benefits of tranching are not uniform but rather AUM-dependent, with larger AUMs benefiting more than smaller ones.

In other words, while all categories of investors should be aware of the effects caused by rebalance timing luck (RTL), we think each category should address the problem differently. Generally, smaller retail investors would benefit most from accepting a relatively high exposure to RTL, as their limited capital is greatly affected by the increased trading activity that portfolio tranching entails. In contrast, institutional investors involved in the design of factor-based investment vehicles (who can easily absorb the additional operational and infrastructure burden) can successfully embrace tranching as an effective countermeasure against rebalance timing luck.

Nevertheless, our findings also highlight the inherent difficulty of working with momentum strategies, where rankings, especially for concentrated portfolios, can fluctuate substantially even over short horizons. Further research should investigate alternative momentum definitions capable of generating more stable rankings over time.

Author Biography

Carlo Zarattini

Originally from Italy, Carlo Zarattini currently resides in Lugano, Switzerland. After completing his mathematics degree in Padova, he pursued a dual master's in quantitative finance at Imperial College London and USI Lugano. He formerly served as a quantitative analyst at BlackRock, where he developed volatility and trend-following trading strategies. Carlo later founded Concretum Group, a quantitative research boutique supporting institutional clients in the design and implementation of high- and medium-frequency systematic strategies across equities, futures, and options. He is also the founder of R-Candles.com, the first backtesting platform designed specifically for discretionary technical traders.

Carlo is currently ranked among the top 100 authors on SSRN, with more than 150,000 downloads since 2023. His research on trend-following, intraday trading, and volatility strategies is known for combining academic rigor with clear, intuitive explanations that make quantitative finance accessible to a broad audience. His work has received multiple industry recognitions, including awards from Quantpedia (2024, 2025), the Diaman Award (2025), and the prestigious CMT Association's Charles H. Dow Award (2025).

Alberto Pagani

Alberto earned his master's degree in Management Engineering from the University of Parma. Some of his achievements include being listed in the National Registry of Excellence by the Ministry of Education, University, and Research (MIUR) in 2020, and having one of his research papers honored with the Diaman Award in 2025. He currently serves as a quantitative researcher at Concretum Group.

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