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Machine Learning in Asset Pricing: Performance and Implementation around the Globe



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ABSTRACT

We evaluate the performance of the Artificial Intelligence Pricing Theory (AIPT) framework across global equity markets, with particular focus on implementation. Relative to linear benchmark models, AIPT often delivers approximately 10% higher gross information ratios, suggesting that non-linear specifications can extract additional predictive information from firm characteristics. However, these gains are not robust across regions and weaken materially after transaction costs are incorporated. The primary limitation is approximately 20% higher portfolio turnover, which erodes net performance and limits implementation efficiency. We further show that techniques designed to reduce turnover improve net performance but attenuate alpha generation. Overall, our findings highlight a fundamental trade-off between return predictability and implementation efficiency in machine learning-based asset pricing models.

KEY TAKEAWAYS

- Machine learning approaches might deliver strong gross performance but results are not robust across regions
- Predictive gains weaken materially after transaction costs are included as high turnover erodes performance and limits practical implementation
- An investment framework that balances out model complexity and implementation efficiency is essential for machine learning approaches to add value

1. Introduction

Machine learning has become an increasingly prominent component of the empirical asset pricing toolkit, enabling the modeling of non-linear relationships and interaction effects across a large set of firm characteristics. A growing body of literature shows that such methods can improve the modeling of cross-sectional expected returns relative to traditional linear approaches, including Gu, Kelly, and Xiu (2020), Kozak, Nagel, and Santosh (2020), Freyberger, Neuhierl, and Weber (2020), and Chen, Pelger, and Zhu (2024). By accommodating interaction effects and non-linearities, these models expand the set of functional forms available for modeling the cross-section of asset returns. These developments have generated significant academic interest and increased the prominence of machine learning methods in empirical asset pricing research.

However, an important question remains how strong empirical results from academic machine learning research can be translated into robust and implementable systematic investment strategies. One reason is that much of the existing evidence focuses on theoretical (gross) performance, whereas portfolios realize performance only after implementation considerations, including transaction costs. Non-linear models tend to generate unstable signals and require frequent rebalancing, leading to high turnover and substantial transaction costs. Prior work has highlighted this issue, with Avramov, Cheng, and Metzker (2023) documenting elevated turnover in machine learning-based portfolios, and DeMiguel et al. (2020), Li et al. (2020), Chen and Velikov (2023), and Detzel, Novy-Marx, and Velikov (2021) showing that implementation costs can materially alter the attractiveness of trading strategies.

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> ***The value of machine learning in asset pricings depends not only on prediction accuracy, but also on implementation efficiency***

A second challenge relates to robustness across markets. Much of the machine learning literature in asset pricing is based on U.S. data, raising concerns about the generalizability of results.

As noted by Karolyi (2016), the "academic home bias" remains pervasive in empirical finance, with limited evidence outside the U.S. Studies such as Cakici et al. (2024), Hanauer and Kalsbach (2023), and Hellum, Jensen, Kelly, and Pedersen (2025) show that performance can vary meaningfully across regions. Differences in market structure, data quality, and investment universes introduce additional complexity, making global implementation materially more challenging.

In this paper, we evaluate the Artificial Intelligence Pricing Theory (AIPT) framework (Didisheim et al., 2025) as a flexible approach to modeling the relationship between firm characteristics and asset returns. Unlike linear models, AIPT allows for a non-linear mapping from characteristics to portfolio weights using a high-dimensional feature representation. This design enables the model to capture non-linearities and interaction effects across signals that are excluded by construction in standard linear approaches. At the same time, it introduces challenges related to stability, interpretability, and implementation.

We assess the performance of AIPT along two key dimensions. First, we examine whether the model delivers consistent improvements in risk-adjusted returns over linear benchmarks and across multiple regions. Second, we evaluate whether these improvements persist after accounting for transaction costs and implementation frictions. This dual focus is critical, as it directly addresses the gap between academic evidence and real-world implementability. Essentially, we explicitly frame the problem as a trade-off between predictive performance and implementation efficiency.

Our results show that AIPT delivers strong gross performance in several markets, outperforming linear benchmarks in four out of six regions. However, these gains are not consistent across geographies and weaken materially once transaction costs are incorporated. High portfolio turnover emerges as a central limitation, eroding net returns and eliminating most of the apparent advantages over simpler models, particularly in higher-capacity implementation settings where trading frictions may become more pronounced. Further analysis shows that a significant portion of AIPT's performance can be explained by some exposure to traditional factors, particularly momentum and quality, consistent with evidence that non-linear models often recover well-known return patterns.

We also evaluate several adjustments designed to reduce turnover and improve implementation efficiency. Techniques such as forecast smoothing and extending prediction horizons reduce turnover and improve net performance, but at the cost of lower alpha. This highlights a fundamental trade-off: increasing model flexibility enhances return predictive power but leads to higher trading costs, while stabilizing the model improves implementation efficiency but reduces performance. The results therefore stress that the central challenge of ML models extends beyond prediction accuracy to the implementation properties of the model itself.

Our findings show that the value of machine learning in asset pricing depends not only on predictive performance, but also on the ability to retain performance after implementation costs. Consistent with Gupta, Raol, and Roscovan (2022), new modeling approaches should be evaluated within an investment framework that explicitly accounts for implementation costs and portfolio construction constraints. In this context, machine learning is best viewed as a complementary extension to existing systematic investment approaches rather than a standalone replacement.

2. Methodology

This section discusses the key elements of our analysis: investment framework, model design and implementation, as well as data, portfolio construction, and evaluation. Our objective is to illustrate the main mechanisms underlying the framework while deferring the technical details to the appendix for the interested reader.

2.1. Investment framework

Our empirical framework is designed to isolate how different modeling approaches translate firm-level characteristics into portfolio weights and, ultimately, into investment performance. Across all specifications, we rely on a common set of inputs consisting of firm characteristics typically associated with Value, Momentum, and Quality factors.

The central distinction lies not in the information set, but in how characteristics are translated into portfolio weights

These characteristics are well established in the empirical asset pricing literature as key drivers of cross-sectional returns (Fama and French, 1993, 2015; Daniel and Titman, 1997). By holding the information set fixed, we ensure that differences in performance can be attributed directly to the modeling approach rather than to variations in inputs. This design is critical for drawing meaningful conclusions about the incremental value of machine learning.

The central distinction in our analysis lies in how characteristics are mapped into portfolio weights. Traditional linear approaches impose a fixed and additive structure, where each characteristic contributes independently to expected returns. This formulation underpins a large class of empirical models, including standard cross-sectional regressions and factor-based portfolio construction (Fama and French, 1993; Kozak, Nagel, and Santosh, 2020). While this structure is transparent and easy to control, it restricts the model's ability to capture interactions and higher-order effects across signals. As a result, linear models may leave economically relevant information unexploited.

In contrast, machine learning approaches allow for non-linear and interaction mappings between characteristics and portfolio weights, capturing interactions and non-linear relationships that are excluded by construction in linear frameworks (Gu, Kelly, and Xiu, 2020; Freyberger, Neuhierl, and Weber, 2020). This flexibility expands the space of potential return drivers and can improve predictive performance in-sample. However, it also introduces greater sensitivity to noise, as small changes in inputs can lead to large changes in portfolio weights. From an investment perspective, this increased responsiveness creates a direct tension between predictive power and stability, with important implications for turnover and implementation costs.

Importantly, we do not impose a factor structure ex-ante in the machine learning setting. While linear models typically interpret characteristics as proxies for a small number of systematic factors, recent work shows that characteristics can also be viewed more generally as sufficient statistics for expected returns (Kelly, Pruitt, and Su, 2019). The AIPT framework builds on this perspective by treating characteristics as direct inputs into a return-generating process, allowing factor exposures to emerge endogenously. This distinction is economically meaningful, as it allows us to assess whether machine learning uncovers genuinely new sources of return or primarily re-expresses known factor premia in a more complex form. It also provides a cleaner lens through which to evaluate the true contribution of model flexibility.

2.2. Model implementations

We begin with a set of linear benchmark models that serve as a natural and economically interpretable point of comparison. In this setting, expected returns are modeled as linear functions of firm characteristics, implying that each signal contributes independently and additively to portfolio construction. Our primary benchmark is a risk-weighted multi-factor portfolio, which combines Value, Momentum, and Quality signals while explicitly controlling for risk contributions (Gupta, Sun, and Zou, 2022). In addition, we estimate ordinary least squares and ridge regression specifications, where the latter introduces regularization to mitigate overfitting and stabilize estimates in the presence of correlated characteristics (Kozak, Nagel, and Santosh, 2020). These models provide a transparent and well-understood baseline against which the incremental value of non-linear approaches can be assessed.

The AIPT framework departs from these linear specifications by allowing for a non-linear mapping from characteristics to portfolio weights. Rather than directly modeling expected returns in a linear form, the approach constructs portfolios through a high-dimensional transformation of the input characteristics, enabling the model to capture interactions and higher-order effects. Conceptually, this aligns with recent advances in machine learning asset pricing that emphasize non-linear functional forms and large feature spaces (Gu, Kelly, and Xiu, 2020; Bryzgalova, Pelger, and Zhu, 2021; Kelly, Malamud, and Zhou, 2024). At the same time, the framework imposes structure on the non-linear specification, improving estimation stability and implementation feasibility relative to fully unconstrained approaches. This balance between expressiveness and structure is central to its appeal from an implementation perspective.

To benchmark AIPT against a fully flexible and unconstrained non-linear alternative, we also implement a neural network model using the same set of input characteristics. The network is trained to predict future returns through a non-linear function of the inputs, allowing for non-linear relationships and interaction effects similar to AIPT but learned directly through optimization (Chen, Pelger, and Zhu, 2024). This approach represents a higher degree of flexibility, as the functional form is not constrained ex-ante and is instead determined entirely by the data. However, this additional flexibility comes at the cost of greater instability and higher sensitivity to estimation noise. In practice, this distinction allows us to isolate the role of structure in non-linear modeling by comparing controlled flexibility, as in AIPT, with unconstrained flexibility, as in standard deep learning approaches.

Ultimately, the three model classes define a clear spectrum of complexity. Linear models provide maximum transparency and stability but limited flexibility. Neural networks offer maximum flexibility but can be difficult to control and implement in practice. AIPT occupies an intermediate position, combining non-linear expressiveness with a structured design that aims to balance predictive performance and robustness.

This positioning is central to our empirical analysis, as it allows us to evaluate whether controlled flexibility can deliver a more attractive trade-off between alpha and implementation efficiency than either extreme.

2.3. Data, portfolio construction, and evaluation

All models are estimated within a consistent data and implementation framework to ensure comparability across specifications. Our dataset spans December 1996 to June 2024 and covers six major equity regions: the United States, the United Kingdom, Japan, Australia, Continental Europe, and Emerging Markets. We restrict the investment universe to large- and mid-cap stocks and exclude financial firms to enhance comparability across regions and reduce the influence of illiquid securities.[1] Firm characteristics are standardized cross-sectionally each month, ensuring that signals are comparable across assets and robust to outliers. This consistent setup allows us to attribute differences in performance directly to model design rather than to data or universe effects.

Non-linear model estimation follows a rolling-window approach, where parameters are estimated using the preceding ten years of data and evaluated out-of-sample from February 2007 to June 2024. Portfolio weights are constructed on a monthly basis and adjusted to be both market- and industry-neutral, ensuring that performance reflects characteristic-driven signals rather than unintended exposures. This design aligns with standard empirical asset pricing methodologies (Fama and French, 2015; Kelly and Xiu, 2023) while maintaining a strong link to practical portfolio construction. Importantly, it allows for a clean separation between signal generation and portfolio implementation. As a result, the reported performance reflects the economic value of the signals (and their combination thereof) rather than structural biases.

Transaction costs and turnover play a central role in our evaluation. We incorporate trading costs of 25 basis points in developed markets and 50 basis points in emerging markets, reflecting regional differences in liquidity and market structure. Turnover is measured as the extent of portfolio rebalancing required over time and provides a direct link between model flexibility and implementation costs. This is particularly important in the context of machine learning models, where higher responsiveness can translate into materially higher trading activity. Our approach follows prior work emphasizing the importance of trading frictions when evaluating anomaly strategies and machine learning models (DeMiguel et al., 2020; Detzel, Novy-Marx, and Velikov, 2021; Chen and Velikov, 2023).

Finally, to address the sensitivity of machine learning models to parameter choices, we evaluate AIPT across a range of hyperparameter configurations and random initializations. Rather than focusing on a single specification, we report average performance across these configurations, providing a more robust and representative assessment of model behavior. This approach reduces the risk that results are driven by favorable parameter choices and aligns the analysis with practical implementation, where stability is as important as peak performance. It also reflects recent recommendations in the literature to emphasize robustness and reproducibility when evaluating non-linear models (Bryzgalova, Pelger, and Zhu, 2021; Jensen et al., 2024).

3. Key Findings

This section evaluates the performance of the AIPT framework across regions, with a focus on both gross and net investment outcomes. A central objective of the analysis is to assess whether improvements in predictive performance translate into economically meaningful gains after accounting for implementation frictions. To ensure comparability across markets, we incorporate transaction costs of 25 basis points in Developed Markets and 50 basis points in Emerging Markets, reflecting differences in liquidity and trading conditions. While a full modeling of transaction costs and market impact is beyond the scope of this paper, these assumptions are broadly consistent with prior empirical studies and are intended to illustrate the implementation consequences of higher turnover across model specifications. As such, the analysis should be interpreted as a comparative assessment of implementation efficiency rather than a precise estimate of realized trading costs. This framework allows us to distinguish between theoretical performance and realizable investment outcomes after implementation costs. Throughout the section, results are therefore interpreted through the trade-off between return predictability and implementation efficiency.

[1] This restriction is particularly important in the context of machine learning models, where predictive signals are often strongest in smaller and less implementable segments of the cross-section (DeMiguel et al., 2020, Chen and Velikov, 2023, Jensen et al., 2024). Focusing on more liquid securities therefore provides a more realistic assessment of whether non-linear models can generate investable performance after implementation costs.

[2] These assumptions are broadly consistent with estimates commonly used in the empirical asset pricing and implementation literature and are intended to reflect average implementation costs for diversified institutional portfolios across regions and through longer periods of time. Actual transaction costs may vary depending on market conditions, portfolio capacity, execution methodology, and investment universe.

3.1. Performance Across Markets

We begin by evaluating out-of-sample performance across six major equity regions and their average. Table 1 reports gross returns, risk, information ratios, turnover, and net performance for all model specifications. This comprehensive view allows us to assess not only return predictability but also the extent to which performance survives realistic implementation costs. By presenting both gross and net metrics side by side, the table directly highlights the gap between theoretical and realized investment performance.

This distinction is central to interpreting the results that follow. A clear pattern emerges from the average results across regions. Non-linear models, particularly AIPT, generally deliver stronger theoretical gross performance than linear benchmarks, as reflected in roughly 10% higher gross information ratios on average. However, these gains are accompanied by materially higher turnover of roughly 20% higher on average, which substantially reduces net performance after

Table 1. Out-of-sample performance comparison of the AIPT ML framework versus benchmark models across six global equity regions.

Panel (a) reports Annualized Gross Returns (%), Panel (b) shows Annualized Risk (%), Panel (c) presents Gross Information Ratios (Gross IR), Panel (d) presents Annualized one-way Portfolio turnover (%), Panel (e) reports Annualized Net Returns (%) and Panel (f) presents Net Information Ratios (Net IR). Benchmarks include the risk-weighted multi-factor portfolio (RW), a linear multi-factor portfolio (OLS), a regularized linear multi-factor portfolio (RR), and a neural network multi-factor portfolio (NN). All portfolios are rebalanced monthly from February 28, 2007, to June 30, 2024, and assumes trading costs of 25 bps in Developed Markets (US, UK, Japan, Australia, Europe) and 50 bps in EMM. All models are trained on a 10-year rolling window starting December 1999. Performance results of all portfolios are reported for out-of-sample evaluation period spanning February 2007 to June 2024. Simulated past performance is not a guarantee of future returns. Returns are in USD gross of management fees and dividends, unless otherwise stated. All results are hypothetical and for academic illustration only.

Model	US	UK	Japan	Australia	Emerging Markets	Europe ex. UK	Average
Panel (a): Annualized Gross Returns (%)							
AIPT	3.77	5.66	3.57	2.73	7.48	5.29	4.75
RW	3.61	8.75	1.97	4.18	7.93	5.44	5.31
OLS	5.01	9.28	5.13	4.26	10.27	8.25	7.03
RR	5.09	9.95	2.59	5.11	8.94	7.97	6.61
NN	0.41	4.10	4.52	4.05	6.54	5.94	4.26
Panel (b): Annualized Risk (%)							
AIPT	3.22	6.30	3.68	8.24	4.37	3.66	4.91
RW	5.46	6.95	4.70	9.89	4.60	4.62	6.04
OLS	5.48	8.21	7.03	11.17	6.33	6.42	7.44
RR	5.62	8.43	5.25	10.46	6.22	6.03	7.00
NN	5.67	7.96	6.09	10.47	5.64	4.80	6.77
Panel (c): Gross Information Ratio (Gross IR)							
AIPT	1.17	0.9	0.97	0.33	1.71	1.45	1.09
RW	0.66	1.26	0.42	0.42	1.72	1.18	0.94
OLS	0.91	1.13	0.73	0.38	1.62	1.28	1.01
RR	0.91	1.18	0.49	0.49	1.44	1.32	0.97
NN	0.07	0.52	0.74	0.39	1.16	1.24	0.69
Panel (d): Annualized Turnover (one-way, %)							
AIPT	587	517	579	595	520	475	545
RW	358	391	380	516	451	390	414
OLS	549	514	566	619	592	520	560
RR	498	444	459	531	517	466	485
NN	1,338	1,155	1,293	1,152	1,236	1,226	1233
Panel (e): Annualized Net Returns (%)							
AIPT	0.84	3.08	0.68	-0.25	2.28	2.92	1.59
RW	1.82	6.79	0.07	1.60	3.42	3.49	2.87
OLS	2.27	6.71	2.30	1.17	4.35	5.65	3.74
RR	2.60	7.73	0.30	2.46	3.77	5.64	3.75
NN	-6.28	-1.68	-1.95	-1.71	-5.82	-0.19	-2.94
Panel (f): Net Information Ratio (Net IR)							
AIPT	0.26	0.49	0.18	-0.03	0.52	0.80	0.37
RW	0.33	0.98	0.02	0.16	0.74	0.76	0.50
OLS	0.41	0.82	0.33	0.10	0.69	0.88	0.54
RR	0.46	0.92	0.06	0.23	0.61	0.94	0.54
NN	-1.11	-0.21	-0.32	-0.16	-1.03	-0.04	-0.48

Non-linear models often improve theoretical performance, but retain a smaller share of returns after implementation costs

implementation costs. In contrast linear models generate lower gross performance but retain a larger share of returns after costs due to lower trading intensity. This distinction between theoretical and realized performance represents the central empirical results of the paper.

Zooming into the performance across regions before accounting for transaction costs, AIPT delivers higher gross information ratios than linear benchmarks in several regions. In particular, the model outperforms linear benchmarks in the United States, Japan, Emerging Markets, and Europe ex-UK, achieving higher gross information ratios than both the risk-weighted (RW) and regression-based (OLS) portfolios. These results indicate that the flexible non-linear structure of AIPT is able to capture interactions across characteristics that are not exploited by linear models.

Performance, however, is not uniform across markets. In the United Kingdom and Australia, linear benchmark models outperform AIPT, highlighting meaningful regional variation in model effectiveness. As AIPT outperforms in four out of six regions in gross terms, this highlights its predictive gains are present but not consistently robust. This lack of consistency is important from an investment perspective, as it limits the reliability of the model when applied in a global context. It also reinforces concerns around the generalizability of machine learning results beyond the U.S. market. In practice, this variability reduces confidence in the stability of the non-linear signal.

Once transaction costs are incorporated, the relative performance of AIPT deteriorates materially. Net information ratios fall below those of linear benchmarks in most regions and become negative in some cases. These results indicate that improvements in theoretical gross performance do not translate reliably into realized net investment outcomes after implementation costs. The impact is particularly visible in regions with higher turnover or weaker gross performance, where costs fully offset predictive gains. The reversal in model rankings after costs further highlights the importance of implementation efficiency when evaluating non-linear asset pricing models.

Overall, the results in Table 1 highlight a clear disconnect between theoretical performance and realizable investment outcomes. While AIPT often improves gross performance relative to linear benchmarks, these gains are highly sensitive to implementation costs arising from elevated turnover. In contrast, simpler linear models deliver more stable net performance across regions, despite lower theoretical performance. The evidence therefore suggests that increased model complexity does not necessarily translate into superior realized investment outcomes.

3.2. Turnover and Implementation Costs

The deterioration in net performance is closely linked to portfolio turnover. As shown in Table 1 (Panel d), AIPT exhibits substantially higher turnover than linear benchmark models across all regions. This pattern is consistent and economically large, implying substantially greater trading activity and implementation costs. This relationship between model complexity, trading intensity, and net performance is central to understanding the economic limitations of non-linear assert pricing models.

The magnitude of turnover differences is material. In the United States, for example, AIPT turnover reaches 587%, compared to 358% for the risk-weighted benchmark portfolio. Similar patterns are observed across all other regions, with AIPT consistently exceeding linear benchmarks by a wide margin. The neural network (NN) model represents an extreme case, with turnover exceeding 1,100% in every market. These levels of trading activity imply substantial implementation costs and help explain the sharp deterioration in net performance observed for non-linear models.

This elevated turnover reflects the sensitivity of non-linear models to small changes in input characteristics. Because machine learning models allow interactions effects and non-linearities, relatively small variations in signals can generate large changes in portfolio weights. While this responsiveness can improve in-sample fit and short-term prediction, it also introduces instability in portfolio construction. In effect, the model continuously re-optimizes in response to noise as well as signal. This behavior translates directly into higher trading frequency and increased implementation costs.

Again, once these costs are incorporated, the impact on performance is substantial. As shown in Table 1 (Panels e and f), net returns and information ratios for AIPT are consistently lower than those of linear benchmarks models across most regions. In contrast, the neural network specification performs particularly poorly after costs, producing negative net returns in all markets, highlighting the severe implementation challenges associated with unconstrained flexibility. Relative to the neural network model, AIPT demonstrates that imposing additional structure of non-linear specifications can, to an extent, improve implementation efficiency, although not sufficiently to outperform simpler linear models on a consistent net basis.

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Table 2. Annualized alpha (%) estimates from regressions of AIPT portfolio returns on benchmark models.

Panel (a) presents the spanning alphas using gross returns and Panel (b) presents the spanning alphas using net returns. The alphas are reported relative to the RW multi-factor portfolio returns, linear multi-factor portfolio (OLS), a regularized linear multi-factor portfolio (RR), and a neural network portfolio returns (NN) spanning from February 2007 to June 2024. Positive alphas indicate incremental performance unexplained by the corresponding benchmark. Statistical significance levels are indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.10. Simulated past performance is not a guarantee of future returns. All results are hypothetical and for academic illustration only.

Model	US	UK	Japan	Australia	Emerging Markets	Europe ex. UK
Panel (a): Gross Returns						
alpha (RW)	2.34***	-0.31	2.67***	0.39	1.27*	2.11***
alpha (OLS)	1.92***	0.27	1.54**	0.04	1.85**	2.06***
alpha (RR)	2.21***	0.00	2.05***	-0.59	2.57***	1.69**
alpha (NN)	3.85***	4.18***	2.98***	0.92	4.87***	4.20***
Panel (b): Net Returns						
alpha (RW)	0.05	-1.5	0.41	-1.17	-0.72	0.83
alpha (OLS)	-0.04	-0.78	-0.27	-1.26	-0.15	0.69
alpha (RR)	-0.06	-1.32	0.20	-1.99	0.05	0.31
alpha (NN)	2.08***	3.91***	0.68	0.20	4.99***	2.95***

3.3. Spanning Tests

To assess whether AIPT delivers incremental value beyond benchmark models, we conduct spanning tests. Specifically, we regress AIPT portfolio returns on a set of linear and non-linear benchmark portfolios and examine the resulting alphas. Table 2 reports annualized alpha estimates for both gross and net returns across all regions. This framework allows us to determine whether AIPT captures return components that are not explained by either linear benchmarks or alternative non-linear specifications. In doing so, the analysis distinguishes between the incremental contribution of non-linearity itself and the contribution of the structured AIPT architecture relative to less constrained machine learning specifications.

Using gross returns, AIPT generates positive and statistically significant alphas in several regions, including the United States, Japan, Emerging Markets, and Europe ex-UK. These results indicate that the model captures return patterns that are not fully explained by linear benchmark portfolios. However, the evidence is not uniform across markets, with limited or negative alpha observed in the United Kingdom and Australia. Consistent with earlier results, this regional heterogeneity raises questions about the robustness of non-linear asset pricing models across global markets.

Once transaction costs are incorporated, the spanning results weaken substantially. Net alphas relative to linear benchmarks are generally insignificant or negative across regions, indicating that the incremental performance observed in gross terms does not persist after implementation costs when benchmarked against linear models. These findings reinforce the earlier evidence that improvements in theoretical return predictability do not reliable translate into superior realized net investment outcomes.

Relative to the neural network benchmark, AIPT delivers positive and often significant alphas in most regions, both before and after costs. This suggests that while both approaches capture non-linearities, AIPT provides a more stable and implementable alternative to unconstrained machine learning models. The comparison therefore highlights that the economic value of non-linearity depends not only on predictive capacity, but also on how the model is structured and implemented.

Overall, the spanning results reinforce the distinction between theoretical and realized performance in non-linear asset pricing models. While AIPT often generates positive gross alpha relative to benchmark specifications, these gains weaken substantially once implementation costs are incorporated. At the same time, the model compares favorably to fully unconstrained neural network architectures, indicating that some degree of structure can

improve the economic viability of non-linear approaches. The evidence therefore highlights that the effectiveness of machine learning models depends not only on predictive performance, but also on implementation efficiency and turnover management. Without this, incremental alpha remains largely theoretical.

Table 3. AIPT Factor Loadings

The table shows annualized alpha (%) estimates, factor loadings and out-of-sample R-squared from regressions of gross AIPT portfolio returns on gross Momentum (MOM), Quality (QAL) and Value (VAL) factor portfolio returns spanning from February 2007 to June 2024. The table reports alphas relative to the multivariate setup and the factor loadings. Statistical significance levels are indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.10. Simulated past performance is not a guarantee of future returns. All results are hypothetical and for academic illustration only.

Coefficient	US	UK	Japan	Australia	Emerging Markets	Europe ex. UK
$\hat{\alpha}$	2.65***	-1.08	2.38***	-0.72	0.91	0.61
$\hat{\beta}_{MOM}$	0.21***	0.37***	0.11***	0.41***	0.51***	0.31***
$\hat{\beta}_{QAL}$	0.05	0.28***	0.09	0.29***	0.06	0.38***
$\hat{\beta}_{VAL}$	0.23***	0.38***	0.34***	0.11**	0.45***	0.19***
R^2 (%)	40.5	63.7	32.2	49.5	70.2	59.0



A meaningful share of machine learning performance reflects known factor premia expressed through more complex functional forms

3.4. Dissecting AIPT Through a Factor Lens

To better understand the drivers of AIPT performance, we analyze its exposure to traditional factors. Table 3 reports results from regressions of AIPT returns on Momentum, Quality, and Value factor portfolios across regions. This analysis allows us to assess whether the model generates genuinely new sources of return or primarily reflects exposure to established factor premia. By decomposing returns in this way, we move beyond performance attribution and focus on economic interpretation. This is particularly important given the flexibility of machine learning models.

A key result is that AIPT exhibits strong and statistically significant exposure to Momentum across all regions. These loadings are consistently positive and economically sizeable, indicating that momentum-related dynamics play an important role in driving performance. At the same time, exposures to Quality and Value are also often significant, although less consistent across regions. In several markets, these additional factor loadings are comparable in magnitude to momentum, in a more balanced factor profile. Overall, AIPT appears to combine multiple sources of return rather than relying on a single dominant driver.

This interpretation is reinforced by the explanatory power of the regressions. A substantial portion of return variation is captured by traditional factors, with R-squared values ranging from 40% to 70% across regions. However, a non-trivial residual component remains, indicating that

Table 4. AIPT and Factor Correlations

The table shows annualized alpha (%) estimates, factor loadings and out-of-sample R-squared from regressions of gross AIPT portfolio returns on gross Momentum (MOM), Quality (QAL) and Value (VAL) factor portfolio returns spanning from February 2007 to June 2024. The table reports alphas relative to the multivariate setup and the factor loadings. Statistical significance levels are indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.10. Simulated past performance is not a guarantee of future returns. All results are hypothetical and for academic illustration only.

Factor	US	UK	Japan	Australia	Emerging Markets	Europe ex. UK
MOM	0.30	0.50	0.05	0.57	0.59	0.47
QAL	0.44	0.57	0.05	0.44	0.40	0.58
VAL	0.35	0.32	0.50	0.18	0.30	0.08

AIPT is not fully spanned by standard factor models. This suggests that the model, as expected, captures additional non-linear effects beyond traditional linear factor exposures. The economic relevance of these residual components, however, must be assessed in light of implementation costs.

To complement the regression analysis, we examine correlations between AIPT returns and individual factor portfolios in Table 4. The results confirm that AIPT is consistently related to Momentum, with relatively high correlations observed in most regions. However, correlations with Quality are also substantial and, in some cases, comparable in magnitude. Value plays a more limited but still non-negligible role. Taken together, these patterns indicate that AIPT's return profile reflects a combination of well-known factor exposures rather than a single dominant source.

These findings have important implications for interpreting performance. First, they suggest that a meaningful portion of AIPT's returns can be explained by traditional factor premia, particularly momentum and quality-related effects. Second, they highlight that part of the model's apparent

Reducing turnover improves implementation efficiency, but often weakens the very signals that generate alpha

complexity may reflect a re-expression of known return drivers in a more flexible functional form. At the same time, the presence of residual returns indicates that the model does capture additional structure. However, as shown in earlier sections, these incremental effects are not sufficient to offset the costs associated with higher turnover.

Overall, the factor analysis reinforces a nuanced conclusion. AIPT does not simply replicate a single factor, but nor does it generate entirely novel sources of return. Instead, it combines established factor exposures with additional non-linear components, the economic value of which is limited by implementation frictions. From an investment perspective, this raises the question of whether similar exposures could be achieved more efficiently using simpler and more transparent approaches.

4. Turnover Mitigation and Trade-offs

A central finding of Section 3 is that the performance of machine learning-based portfolios is heavily constrained by turnover. While AIPT delivers strong gross performance in several regions, high trading intensity materially erodes net returns once implementation costs are considered. This section evaluates whether these constraints can be mitigated through simple, implementable adjustments to the modeling framework. The objective is not to improve predictive performance per se, but to enhance the economic value of the signals by reducing trading frictions. In doing so, we explicitly analyze the trade-off between alpha and implementation efficiency.

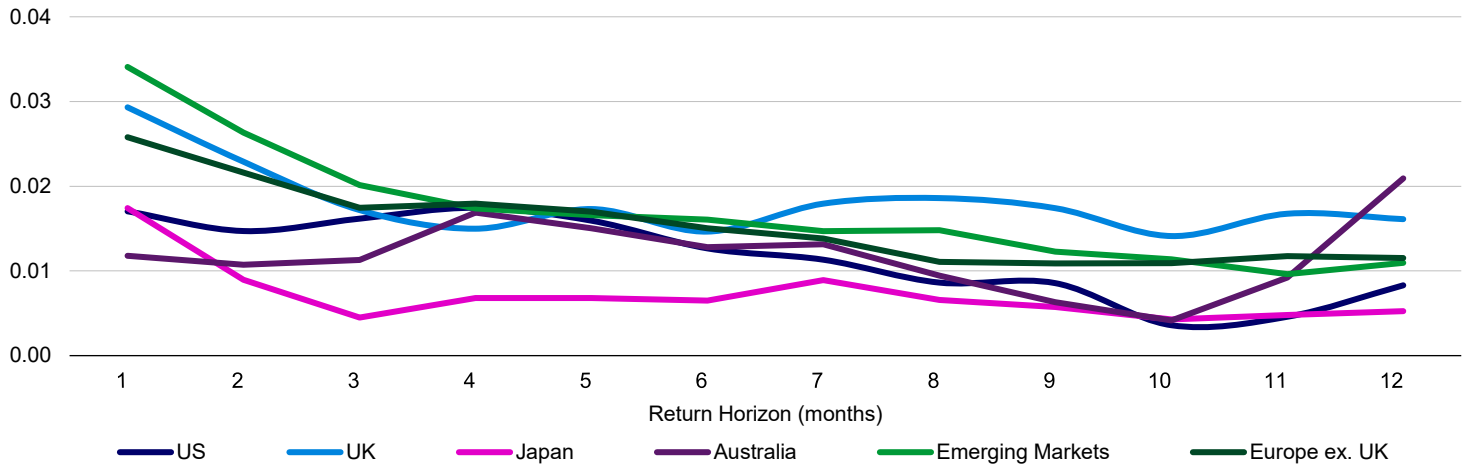
We focus on two complementary approaches: (i) smoothing model forecasts over time and (ii) extending forecast horizons. Both techniques aim to stabilize portfolio weights and reduce sensitivity to short-term fluctuations in model inputs. From an economic perspective, these approaches impose discipline on otherwise highly reactive signals, limiting excessive rebalancing. However, this stabilization comes at a cost, as it may dampen the model's ability to capture short-lived return opportunities. As a result, both approaches provide a natural setting to evaluate the trade-off between dynamic responsiveness and robustness.

4.1. Forecast Averaging

A natural approach to reducing turnover is to smooth model forecasts over time. Machine learning signals are often highly responsive to short-term fluctuations in input characteristics, which can introduce noise and lead to excessive trading. By averaging forecasts across periods, the model becomes less sensitive to transitory variation and produces more stable

Figure 1: AIPT Information Coefficients

The chart below plots the lagged Information Coefficients (IC) of AIPT model across regions over different return horizons.



Source: Invesco. Simulated past performance is not a guarantee of future returns. All results are hypothetical and for academic illustration only.

portfolio weights. From an implementation perspective, this directly targets one of the primary weaknesses of non-linear models. The key question is whether this stabilization can be achieved without materially degrading predictive performance.

To guide the choice of smoothing window, we examine the persistence of model signals using lagged information coefficients (ICs), defined as the correlation between past portfolio weights and future returns. Figure 1 plots these lagged ICs across regions over different horizons and illustrates the persistence profile of the AIPT signal. The results show that signal persistence is concentrated in the first few months, with ICs remaining positive for up to three months before declining materially. This pattern suggests that moderate smoothing may reduce trading activity

while preserving a meaningful portion of the underlying predictive signal. Based on this evidence, we implement a three-month moving average of model forecasts.

Table 5 reports the impact of forecast averaging on performance and turnover. The results show a substantial reduction in turnover across all regions, with trading activity in several cases

Table 5. Out-of-sample performance of alternative AIPT models

The table shows out-of-sample performance vs Turnover comparison of the smoothed AIPT model using a 3-month moving average of forecasts (AIPT 3m MA), the baseline AIPT model, and the linear RW multi-factor portfolio. Panel (a) shows the gross information ratios, Panel (b) presents turnover percentages and Panel (c) shows the net information ratios across six major global equity regions between February 2007 and June 2024. Turnover figures are one-way, annualized. Simulated past performance is not a guarantee of future returns. All results are hypothetical and for academic illustration only.

Model	US	UK	Japan	Australia	Emerging Markets	Europe ex. UK
Panel (a): Gross Information Ratio (Gross IR)						
AIPT (3m MA)	1.20	0.59	0.65	0.32	1.56	1.22
AIPT	1.17	0.90	0.97	0.33	1.71	1.45
RW	0.66	1.26	0.42	0.42	1.72	1.18
Panel (b): Annualized Turnover (one-way, %)						
AIPT (3m MA)	390	326	354	371	357	296
AIPT	587	517	579	595	520	475
RW	358	391	380	516	451	390
Panel (c): Net Information Ratio (Net IR)						
AIPT (3m MA)	0.60	0.33	0.14	0.10	0.72	0.81
AIPT	0.26	0.49	0.18	-0.03	0.52	0.80
RW	0.33	0.98	0.02	0.16	0.74	0.76

approaching levels observed for linear benchmark models. This improvement in stability translates into higher net performance, as lower trading costs allow a larger fraction of gross returns to be retained. In some regions, the improvement in net information ratios is economically meaningful, highlighting the importance of controlling turnover. From a practical perspective, this demonstrates that relatively simple adjustments can materially improve implementation efficiency.

However, these benefits are not costless. While gross performance remains broadly similar,

there is a consistent attenuation of signal strength relative to the baseline AIPT model. This reflects the fact that smoothing dampens both noise and signal, reducing the model's ability to react to short-term opportunities. As a result, the gains in net performance come primarily from reduced costs rather than improved prediction. This trade-off is central: improving stability enhances implementation efficiency but weakens alpha.

Overall, forecast averaging provides a clear illustration of the broader tension in machine learning-based investing. Introducing discipline into the model improves economic outcomes, but at the cost of reduced distinctiveness in the signal. In practice, this suggests that the raw predictive power of non-linear models is not directly usable and must be adjusted to meet implementation constraints. The challenge is therefore not only to generate signals, but to control how they are translated into implementable trades.

4.2. Extending Forecast Horizons

An alternative approach to reducing turnover is to extend the forecast horizon of the model. Instead of predicting one-month-ahead returns, the model is trained to target longer horizons, producing signals that evolve more gradually over time. This inherently reduces sensitivity to short-term fluctuations in input characteristics and leads to smoother portfolio adjustments. From an implementation perspective, the approach embeds stability directly into the signal rather than imposing it ex-post. As a result, it provides a complementary mechanism to forecast averaging for controlling trading intensity.

Table 6 presents the performance of models trained on three-, six-, and twelve-month-ahead returns. The results show a consistent reduction in turnover across all regions as the forecast horizon increases. While the magnitude of the reduction is more gradual than in the case of forecast averaging, it remains economically meaningful given the high baseline turnover of the AIPT model. Longer-horizon models produce more persistent signals, which translate into lower rebalancing frequency. This confirms that part of the turnover problem is linked to the short-term nature of the predictive target.

The impact on performance, however, is more nuanced. Shorter extensions of the forecast horizon, such as three months, preserve much of the model's predictive power and in some

Table 6. Out-of-sample performance of alternative Forward Looking AIPT models

The table shows out-of-sample performance vs Turnover comparison of the AIPT model using 3-month ahead returns (AIPT 3m Fwd), AIPT model using 6-month ahead returns (AIPT 6m Fwd), AIPT model using 12-month ahead returns (AIPT 12m Fwd), the baseline AIPT model, and the RW multi-factor portfolio between February 2007 and June 2024. Panel (a) shows the gross information ratios, Panel (b) presents turnover percentages and Panel (c) shows the net information ratios across six major global equity regions. Turnover figures are one-way, annualized. Simulated past performance is not a guarantee of future returns. All results are hypothetical and for academic illustration only.

Model	US	UK	Japan	Australia	Emerging Markets	Europe ex. UK
Panel (a): Gross Information Ratio (Gross IR)						
AIPT (3m Fwd)	1.24	0.77	0.92	0.39	1.67	1.44
AIPT (6m Fwd)	1.17	0.91	0.72	0.39	1.44	1.46
AIPT (12m Fwd)	1.08	0.85	0.72	0.31	1.34	1.25
AIPT	1.17	0.9	0.97	0.33	1.71	1.45
RW	0.66	1.26	0.42	0.42	1.72	1.18
Panel (b): Annualized Turnover (one-way, %)						
AIPT (3m Fwd)	550	506	505	516	517	458
AIPT (6m Fwd)	532	472	473	486	476	439
AIPT (12m Fwd)	465	447	409	440	448	423
AIPT	587	517	579	595	520	475
RW	358	391	380	516	451	390
Panel (c): Net Information Ratio (Net IR)						
AIPT (3m Fwd)	0.42	0.39	0.26	0.08	0.52	0.86
AIPT (6m Fwd)	0.44	0.57	0.10	0.13	0.41	0.92
AIPT (12m Fwd)	0.50	0.52	0.23	0.08	0.40	0.77
AIPT	0.26	0.49	0.18	-0.03	0.52	0.80
RW	0.33	0.98	0.02	0.16	0.74	0.76

cases even improve gross performance. In contrast, longer horizons lead to a more noticeable decline in information ratios, reflecting the reduced ability of the model to capture short-lived return opportunities. This pattern highlights a fundamental trade-off between responsiveness and stability. As the model becomes less reactive, it also becomes less precise in timing return predictability.

In net terms, the reduction in turnover partially offsets the loss in gross performance. In several regions, net information ratios improve relative to the baseline AIPT model, indicating that lower trading costs can compensate for weaker signals. However, these improvements are not uniform across markets and depend on the balance between cost reduction and signal decay. In some cases, the loss in predictive power dominates, limiting the net benefit. This reinforces the idea that turnover mitigation is necessary but not sufficient for improving investment outcomes.

Overall, extending forecast horizons provides a more structural approach to stabilizing machine learning signals. Unlike smoothing, which filters the output of the model, this approach modifies the objective function itself. While both methods reduce turnover, they operate through different channels and imply different trade-offs. In practice, the results suggest that embedding stability in the signal can improve implementation efficiency, but only within limits. Beyond a certain point, reduced responsiveness leads to a meaningful erosion of alpha.

4.3. Incremental Value Under Turnover Mitigation

To assess whether turnover mitigation preserves the incremental value of AIPT, we repeat the spanning analysis for the modified model specifications. Table 7 reports spanning alphas for the smoothed and extended-horizon variants relative to the same set of benchmark models used in Section 3. This allows us to evaluate whether improvements in net performance are driven by retained alpha or simply by reduced trading costs. In doing so, we maintain a consistent framework for comparing baseline and adjusted models. The focus is therefore on whether implementation improvements come at the expense of distinctiveness in the signal.

The results show that turnover mitigation leads to a clear reduction in incremental alpha. While the smoothed and longer-horizon models retain some positive alpha in gross terms, the magnitude and statistical significance are generally lower than for the baseline AIPT specification. This decline reflects the dampening effect of stabilization techniques on model responsiveness. By reducing sensitivity to short-term variation, these approaches also reduce the model's ability to capture transient return opportunities. As a result, part of the original signal is effectively filtered out.

In net terms, the picture is more balanced but still highlights a trade-off. Lower turnover

improves implementation efficiency and allows a larger share of gross returns to be retained, which in some cases supports more stable net performance. However, the reduction in alpha limits the extent to which these gains translate into meaningful outperformance relative to benchmarks. In several regions, the adjusted models remain competitive but do not consistently deliver statistically significant excess returns. This suggests that turnover mitigation improves usability but does not fully restore economic value.

Table 7. Factor Loadings for alternative AIPT Models

The table shows Annualized alpha (%) estimates, factor loadings and out-of-sample R-squared from regressions of gross AIPT portfolio returns on Momentum, Quality and Value gross factor portfolio returns spanning from February 2007 to June 2024. Panel (a) shows multivariate spanning results for the baseline AIPT model, Panel (b) shows multivariate spanning results for the smoothed AIPT model using a 3-month moving average of forecasts (AIPT 3m MA), Panel (c) shows multivariate spanning results for the AIPT model using a 3-month ahead returns (AIPT 3m Fwd), Panel (d) shows multivariate spanning results for the AIPT model using a 6-month ahead returns (AIPT 6m Fwd) and Panel (e) shows multivariate spanning results for the AIPT model using a 12-month ahead returns (AIPT 12m Fwd). Statistical significance levels are indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.10. Simulated past performance is not a guarantee of future returns. All results are hypothetical and for academic illustration only.

Coefficient	US	UK	Japan	Australia	Emerging Markets	Europe ex. UK
Panel (a) AIPT (Baseline)						
$\hat{\alpha}$	2.65***	-1.08	2.38***	-0.72	0.91	0.61
$\hat{\beta}_{MOM}$	0.21***	0.37***	0.11***	0.41***	0.51***	0.31***
$\hat{\beta}_{QAL}$	0.05	0.28***	0.09	0.29***	0.06	0.38***
$\hat{\beta}_{VAL}$	0.23***	0.38***	0.34***	0.11**	0.45***	0.19***
R^2 (%)	40.48	63.69	32.20	49.51	70.22	59.01
Panel (b) AIPT (3m MA)						
$\hat{\alpha}$	2.62***	-2.86***	1.14	-0.82	0.06	-0.15
$\hat{\beta}_{MOM}$	0.18***	0.38***	0.07**	0.40***	0.52***	0.28***
$\hat{\beta}_{QAL}$	0.11**	0.26***	0.08	0.30***	-0.03	0.38***
$\hat{\beta}_{VAL}$	0.20***	0.39***	0.31***	0.13***	0.48***	0.17***
R^2 (%)	37.39	61.06	30.02	48.10	72.35	54.79
Panel (c) AIPT (3m FWD)						
$\hat{\alpha}$	3.13***	-1.85*	2.58***	-0.28	0.91	0.79
$\hat{\beta}_{MOM}$	0.17***	0.47***	-0.02	0.4***	0.5***	0.33***
$\hat{\beta}_{QAL}$	0.04	0.18***	0.21***	0.35***	0.11**	0.4***
$\hat{\beta}_{VAL}$	0.15***	0.4***	0.22***	0.13***	0.44***	0.12***
R^2 (%)	20.68	65.43	19.30	52.07	66.86	56.54
Panel (c) AIPT (6m FWD)						
$\hat{\alpha}$	3.20***	-1.27	1.82**	-0.45	0.13	0.96
$\hat{\beta}_{MOM}$	0.18***	0.52***	-0.02	0.45***	0.52***	0.33***
$\hat{\beta}_{QAL}$	0.03	0.21***	0.14**	0.37***	0.06	0.41***
$\hat{\beta}_{VAL}$	0.20***	0.37***	0.22***	0.05	0.44***	0.13***
R^2 (%)	22.48	67.54	18.65	48.20	64.40	54.52
Panel (c) AIPT (12m FWD)						
$\hat{\alpha}$	2.84***	-1.54	1.87**	-1.24	0.10	0.18
$\hat{\beta}_{MOM}$	0.07*	0.46***	-0.07*	0.41***	0.46***	0.35***
$\hat{\beta}_{QAL}$	0.27***	0.28***	0.08	0.52***	0.11*	0.47***
$\hat{\beta}_{VAL}$	0.13***	0.34***	0.32***	-0.01	0.47***	0.06*
R^2 (%)	24.15	67.05	31.56	53.92	57.26	58.45

These findings reinforce a central tension in machine learning-based investing. Techniques that enhance implementation efficiency tend to reduce the distinctiveness of model signals, bringing them closer to those generated by simpler approaches. In this sense, stabilization acts as a form of regularization at the portfolio level, trading off complexity for robustness. While this improves practical feasibility, it also narrows the gap between machine learning and traditional models. The implication is that part of the perceived advantage of non-linear models is inherently difficult to preserve under realistic constraints.

Overall, the evidence suggests that turnover mitigation is necessary but not sufficient to unlock the full value of machine learning in asset pricing. While it improves net outcomes, it does so primarily by reducing costs rather than by enhancing predictive content. At the same time, it weakens the model's ability to generate distinct alpha. From an investment perspective, this highlights the importance of designing models that are both predictive and inherently stable, rather than relying on ex-post adjustments to address implementation challenges.

In machine learning asset pricing, prediction and implementation cannot be treated as separate problems

4.4. Summary of Trade-offs

The results in this section highlight a fundamental trade-off in machine learning-based investing. Increasing model flexibility enhances predictive performance but leads to high turnover and significant implementation costs. Conversely, stabilizing the model through forecast averaging or longer prediction horizons reduces trading intensity and improves net outcomes, but at the expense of weaker alpha. This tension is not a byproduct of a specific specification, but a structural feature of non-linear modeling approaches.

From an investment perspective, the key challenge is not maximizing predictive accuracy in isolation, but balancing responsiveness with stability. Models that react aggressively to new information may perform well in frictionless settings but are challenging to implement at scale. In contrast, more stable models are easier to manage but may fail to capture short-lived return opportunities. The optimal design therefore lies between these extremes, where sufficient predictive power is retained without incurring excessive trading costs. Achieving this balance is central to translating machine learning insights into investable strategies.

Overall, our evidence suggests that the economic value of machine learning depends on how effectively this trade-off is managed. Improvements in gross performance are not sufficient if they are accompanied by disproportionate increases in turnover. At the same time, overly aggressive stabilization can eliminate the very signals that drive performance. Successful implementation therefore requires integrating predictive modeling with disciplined portfolio construction, ensuring that signals are both informative and usable in practice.

5. Implications

Machine learning provides a framework for modeling complex non-linear and interaction relationships across firm characteristics, but this flexibility does not automatically translate into better investment outcomes. Across regions, AIPT delivers strong gross performance in several markets, indicating that non-linear models can enhance return prediction. However, these gains are not consistent and weaken materially once transaction costs are taken into account. The gap between gross and net performance is economically significant and cannot be ignored in practice. As a result, return predictability alone is an incomplete measure of model quality.

Both predictive performance and implementation present challenges. While the model captures non-linear interactions, these signals are not uniformly robust across regions and can be sensitive to small changes in inputs. At the same time, this flexibility leads to high portfolio turnover, which materially erodes returns and limits scalability. In practice, this combination reduces the reliability of machine learning signals in a global investment context. One should therefore be cautious in extrapolating academic results to implementable portfolios.

A significant portion of AIPT's performance can be explained by exposure to traditional factors, particularly momentum and quality, alongside some inconsistent contributions from value. This suggests that part of the observed performance reflects well-known return drivers expressed through a more complex modeling framework. While the model does capture additional non-linear effects, these are not sufficient to offset the costs associated with higher turnover. As a result, the incremental value of machine learning remains limited after implementation frictions. This raises the question of whether similar exposures can be achieved more efficiently using simpler approaches.

Turnover management emerges as a central requirement for implementation. Techniques such as forecast smoothing and longer prediction horizons can improve net performance by reducing trading activity, but these improvements come at the cost of reduced alpha. This highlights a structural trade-off between return predictability and implementation efficiency that cannot be fully eliminated. Investors must therefore decide where to position themselves along this spectrum, depending on their tolerance for complexity, cost, and model risk. There is no one-size-fits-all solution.

Overall, machine learning should be viewed as a tool rather than a standalone solution. Its value depends on how effectively it is integrated into a disciplined, cost-aware investment process that prioritizes robustness and scalability. In many cases, simpler and more structured models may deliver more reliable net outcomes, particularly when implementation efficiency is a primary objective. The challenge is not to maximize model complexity, but to ensure that any increase in sophistication translates into tangible economic benefit. Without this, the advantages of machine learning remain largely theoretical.

6. Conclusions

This paper evaluates the AIPT machine learning framework across global equity markets, with a focus on both performance and implementation. While the model delivers strong gross risk-adjusted returns in several regions, these gains are not consistent and do not persist after

accounting for trading costs. High portfolio turnover emerges as the primary limitation, materially eroding net returns and eliminating most of the apparent advantage over traditional linear models. At the same time, performance varies meaningfully across regions, underscoring the importance of robustness when evaluating machine learning approaches in a global setting. Our results highlight a clear disconnect between predictive performance and realizable investment outcomes.

More broadly, the findings show that the value of machine learning in asset pricing depends on its ability to deliver stable and implementable strategies rather than strong predictive performance alone. While non-linear models can capture non-linear relationships and interaction effects, these benefits are often fragile and difficult to realize in practice. A meaningful portion of performance can be attributed to exposure to established factor premia, with limited incremental value after accounting for costs. This reinforces the importance of interpreting machine learning results within a well-defined economic framework. Without this discipline, apparent improvements in performance may be misleading.

From an investment perspective, the central challenge is not simply improving predictive accuracy but retaining performance after implementation costs. Approaches that maximize theoretical return predictability without accounting for turnover are unlikely to deliver robust implementable outcomes at scale. At the same time, overly restrictive specifications may fail to capture economically relevant non-linear effects. The evidence therefore suggests that the economic value of machine learning depends less on model complexity alone and more on the balance between return predictability and implementation efficiency.

Our results point toward several directions for future research. One promising avenue is the development of machine learning architectures that incorporate implementation considerations directly in the modeling objective rather than addressing turnover ex-post through portfolio adjustments. Related approaches may include turnover-aware training procedures, longer-horizon optimization targets, and portfolio construction frameworks that jointly balance predictive performance and trading efficiency. The broader implication is that future progress in machine learning asset pricing Is likely to depend less on increasing model complexity in isolation and more on integrating prediction and implementation within a unified investment framework.

References

Avramov, D., Cheng, S., & Metzker, L. (2023). Machine learning vs. economic restrictions: Evidence from stock return predictability. Management Science, 69(5), 2587-2619.

Berk, J. (2023). Comment on 'The Virtue of Complexity in Return Prediction'. Available at SSRN 4410125.

Britten-Jones, M. (1999). The sampling error in estimates of mean-variance efficient portfolio weights. The Journal of Finance, 54(2), 655-671.

Bryzgalova, S., Pelger, M., & Zhu, H. (2021). Machine learning for asset pricing. Journal of Financial Economics, 141(3), 1027–1056.

Buncic, D. (2025). Simplified: A closer look at the virtue of complexity in return prediction. Available at SSRN 5239006.

Cakici, N., Fieberg, C., Metko, D., & Zaremba, A. (2024). Do anomalies really predict market returns? New data and new evidence. Review of Finance, 28(1), 1-44.

Chen, L., Pelger, M., & Zhu, J. (2024). Deep learning in asset pricing. Management Science, 70(2), 714-750.

Chen, A. Y., & Velikov, M. (2023). Zeroing in on the expected returns of anomalies. Journal of Financial and Quantitative Analysis, 58(3), 968-1004.

Cochrane, J. H. (2001). A rehabilitation of stochastic discount factor methodology.

Cochrane, J. H. (2009). Asset pricing: Revised edition. Princeton university press.

Daniel, K., & Titman, S. (1997). Evidence on the characteristics of cross-sectional variation in stock returns. The Journal of Finance, 52(1), 1–33.

DeMiguel, V., Martin-Utrera, A., Nogales, F. J., & Uppal, R. (2020). A transaction-cost perspective on the multitude of firm characteristics. The Review of Financial Studies, 33(5), 2180-2222.

Detzel, A. L., Novy-Marx, R., & Velikov, M. (2021). Model selection with transaction costs. Available at SSRN, 3805379.

Didisheim, A., Ke, S. B., Kelly, B. T., & Malamud, S. (2025). APT or “AIPT”? The surprising dominance of large factor models (No. w33012). National Bureau of Economic Research.

Fallahgoul, H., Franstianto, V., & Lin, X. (2024). Asset pricing with neural networks: Significance tests. Journal of Econometrics, 238(1), 105574.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3–56.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1–22.

Feng, G., Giglio, S., & Xiu, D. (2020). Taming the factor zoo: A test of new factors. The Journal of Finance, 75(3), 1327–1370.

Feng, X., Gupta, T., Protchenko, S., Roscovan, V., & Sun, J. (2024). Control and transparency in factor portfolio implementation. Journal of Beta Investment Strategies, 15(1).

Freyberger, J., Neuhierl, A., & Weber, M. (2020). Dissecting characteristics nonparametrically. The Review of Financial Studies, 33(5), 2326-2377.

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. The Review of Financial Studies, 33(5), 2223–2273.

Gupta, T., Raol, J., & Roscovan, V. (2022). Factor investing: From theory to practice. Journal of Beta Investment Strategies, 13(4).

Gupta, T., Sun, J., & Zou, H. (2022). Risk-based weighting for better factor investing. Risk & Reward, 04/2022.

Han, Y., He, A., Rapach, D. E., & Zhou, G. (2024). Cross-sectional expected returns: new Fama–MacBeth regressions in the era of machine learning. Review of Finance, 28(6), 1807-1831.

Hanauer, M. X., & Kalsbach, T. (2023). Machine learning and the cross-section of emerging market stock returns. Emerging Markets Review, 55, 101022.

Harvey, C. R., Liu, Y., & Zhu, H. (2016). … and the cross-section of expected returns. The Review of Financial Studies, 29(1), 5–68.

Jensen, T. I., Kelly, B. T., Malamud, S., & Pedersen, L. H. (2024). Machine learning and the implementable efficient frontier. Swiss Finance Institute Research Paper, (22-63).

Kalfa, S. Y., Timmermann, A., & van der Zwan, T. (2025). Overhyped? Can ML Models Reliably Predict Stock Returns. Working paper.

Karolyi, A. G. (2016). Home bias, an academic puzzle. Review of Finance, 20(6), 2049-2078.

Kelly, B. T., & Malamud, S. (2025). Understanding the virtue of complexity. Available at SSRN 5346842.

Kelly, B. T., Pruitt, S., & Su, Y. (2019). Characteristics are covariances: A unified model of risk and return. Journal of Financial Economics, 134(3), 501-524.

Kelly, B., Malamud, S., & Zhou, K. (2024). The virtue of complexity in return prediction. The Journal of Finance, 79(1), 459-503.

Kozak, S., Nagel, S., & Santosh, S. (2020). Shrinking the cross-section. The Review of Financial Studies, 33(7), 3067–3114.

Lettau, M., & Pelger, M. (2020). Factor models and the cross-section of expected returns. Annual Review of Financial Economics, 12, 49–74.

Li, S. A., DeMiguel, V., & Martin-Utrera, A. (2020). Which factors with price-impact costs. Working paper.

Li, Y., Simon, Z., & Turkington, D. (2022). Investable and interpretable machine learning for equities. The Journal of Financial Data Science, 4(1), 54-74.

Liu, F., Huang, X., Chen, Y., & Suykens, J. A. (2021). Random features for kernel approximation: A survey on algorithms, theory, and beyond. IEEE Transactions on Pattern Analysis and Machine Intelligence, 44(10), 7128-7148.

Nagel, S. (2025). Seemingly virtuous complexity in return prediction. Chicago Booth Research Paper, (25-10).

Rahimi, A., & Recht, B. (2007). Random features for large-scale kernel machines. Advances in neural information processing systems, 20.

Rahimi, A., & Recht, B. (2008). Weighted sums of random kitchen sinks: Replacing minimization with randomization in learning. Advances in neural information processing systems, 21.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. Journal of Economic Theory, 13(3), 341–360.

Appendix A: Technical Implementation

A.1. Stochastic Discount Factor Representation

The AIPT framework is formulated within the stochastic discount factor (SDF) approach to asset pricing. Let $r_{i,t+1}$ denote the excess return of asset i at time $t+1$. The SDF, denoted m_{t+1} ,prices assets through the standard no-arbitrage condition:

$$\mathbb{E}_t[m_{t+1}r_{i,t+1}] = 0.$$

Following Cochrane (2001, 2009), the SDF can be represented as a portfolio of traded assets:

$m_{t+1} = w_t^\top r_{t+1}$,

where $w_t \in \mathbb{R}^{N_t}$ denotes a vector of portfolio weights that depend on information available at time t. In the AIPT framework, these weights are modeled as functions of firm-level characteristics, allowing the SDF to vary conditionally across time.

Let $x_{i,t} \in \mathbb{R}^P$ denote the vector of standardized firm characteristics for asset i at time t. The objective is to construct a conditional SDF by mapping these characteristics into portfolio weights:

$$w_{i,t} = f(x_{i,t}),$$

where $f(\cdot)$ is an unknown function capturing the relationship between characteristics and optimal portfolio positions. Unlike linear factor models, which impose a parametric structure on f, the AIPT framework allows for a flexible, non-linear specification.

A.2. Random Fourier Feature Expansion

To approximate the unknown function $f(\cdot)$, the AIPT framework employs Random Fourier Features (RFF). This approach maps the original characteristics into a high-dimensional feature space using randomized non-linear transformations. The objective is to capture non-linear and interactions relationships across characteristics in a computationally efficient manner, while maintaining a linear estimation step.

For each asset i at time t, we construct a set of transformed features $\phi(x_{i,t}) \in \mathbb{R}^K$ using sine and cosine transformations. Specifically, for each feature k, we define:

$$\phi_k(x_{i,t}) = \cos(\gamma {\omega_k}^\top x_{i,t}), \text{and } \sin(\gamma {\omega_k}^\top x_{i,t}),$$

where $\omega_k \sim \mathbb{N}(0, I)$ are independently drawn random vectors and γ is a scaling parameter controlling the smoothness of the transformation. This formulation follows the implementation described in the original AIPT framework.

Each pair of sine and cosine functions constitutes a pair of non-linear features. In our implementation, we generate 3,000 such pairs each month, resulting in a large set of transformed characteristics that capture diverse non-linear interactions across the underlying signals.

The scaling parameter γ plays an important role in determining the behavior of the transformation. Smaller values of γ produce smoother feature mappings that capture broader patterns, while larger values allow the model to capture more localized variation. To ensure a balanced representation of different functional forms, we consider $\gamma \in \{0.5, 1, 2\}$ and allocate an equal number of features to each value.

This transformation is applied uniformly across all assets and characteristics at each time t. The resulting feature representation provides a non-linear approximation to the unknown mapping between characteristics and portfolio weights. Unlike neural networks, where feature transformations are learned through optimization, the RFF approach fixes these transformations ex-ante and estimates only the linear combination of features in subsequent steps. This significantly reduces computational complexity and improves stability, while still allowing the model to capture complex non-linear relationships and interaction effects.

A.3. Construction of Non-Linear Factors

Given the transformed features, the AIPT framework constructs a large set of non-linear factor portfolios. Each factor is defined as a characteristic-managed portfolio, where the weights are given by the transformed features. Specifically, for each feature k, the corresponding factor return at time $t+1$ is defined as:

$$f_{k,t+1} = \sum_{i=1}^{N_t} \phi_k(x_{i,t}) r_{i,t+1}.$$

Stacking across all features yields the vector of factor returns $f_{t+1} \in \mathbb{R}^K$ .These factors capture complex, non-linear and interactions effects between the underlying characteristics and form the building blocks of the AIPT model.

This construction can be interpreted as generating a large set of characteristic-managed portfolios, each representing a different non-linear transformation of the input signals. By combining these factors, the model approximates the unknown return-generating process in a flexible manner. At the same time, the use of a large number of factors introduces the need for dimensionality reduction and regularization in the subsequent estimation step.

A.4. Maximum Sharpe Ratios Regression (MSRR)

Given the vector of non-linear factor returns $f_{t+1} \in \mathbb{R}^K$,the objective is to construct a mean-variance efficient combination of these factors. Rather than directly solving a high-dimensional portfolio optimization problem, the AIPT framework adopts the Maximum Sharpe Ratio Regression (MSRR) approach, which provides a tractable reformulation.

Following Britten-Jones (1999), the weights of the tangency portfolio can be obtained through a regression-based representation. Specifically, the maximum Sharpe ratio portfolio corresponds to the solution of a regression problem in which a constant is projected onto the space spanned by excess returns. Building on this result, Kelly and Xiu (2023) extend the approach to high-dimensional settings, allowing for efficient estimation when the number of factors is large.

In the context of the AIPT framework, the MSRR problem is formulated as:

$$\min_{\theta} ||\mathbf{1} - F\,\theta||^2 \ ,$$

where $F \in \mathbb{R}^{T\times K}$ is the matrix of historical factor returns over a training window of length T, $\theta \in \mathbb{R}^K$ represents the weights assigned to the non-linear factors, and $\mathbf{1} \in \mathbb{R}^T$ is a vector of ones.

This formulation avoids the need to estimate large covariance matrices explicitly and provides a direct way to identify the mean-variance efficient combination of factors. Intuitively, the regression seeks a combination of factors that best approximate a constant payoff, which is equivalent to maximizing the Sharpe ratio of the resulting portfolio.

Given that the number of factors K is large and typically exceeds the length of the estimation window T, the problem is ill-posed and requires regularization. To address this, we introduce a ridge penalty, leading to the following estimator:

$$\hat{\theta} = (F^{\top}F + \lambda I)^{-1}\mathbf{1},$$

where $\lambda > 0$ is the regularization parameter. This penalty stabilizes the estimation and mitigates overfitting, ensuring that the resulting factor combination is well-behaved in out-of-sample applications.

Finally, the estimated factor weights $\hat{\theta}$ are mapped back to asset-level portfolio weights. Using the feature representation at time t, the portfolio weights are constructed as:

$$w_{i,t} = \sum_{k=1}^{K} \hat{\theta}_k \, \phi_k(x_{i,t}).$$

This formulation provides a direct link between the non-linear factor structure and the final portfolio weights. By combining a large number of transformed features through MSRR, the AIPT framework constructs a non-linear yet tractable approximation to the optimal stochastic discount factor.

A.5 Implementation Details and Practical Design Choices

The empirical implementation of the AIPT framework follows a set of design choices that ensure robustness, comparability, and practical relevance. These choices relate to data preprocessing, hyperparameter selection, and estimation procedures, and are aligned with the methodology described in the main text.

Data preprocessing and standardization. All firm-level characteristics are transformed cross-sectionally at each time t using a rank-based normalization. Specifically, for each characteristic, values are ranked across all assets, scaled by the number of non-missing observations, and shifted to lie in the interval $[-0.5, 0.5]$. This transformation emphasizes the relative ordering of characteristics rather than their magnitudes and improves robustness to outliers. The same transformation is applied to the generated non-linear features to maintain consistency in the cross-sectional structure.

In addition, returns are adjusted to remove broad market and industry effects. For each asset, raw returns are first adjusted by subtracting the median return of the corresponding industry. The resulting series is then standardized cross-sectionally and orthogonalized with respect to industry dummy variables and market beta. This ensures that the final portfolios reflect characteristic-driven signals rather than unintended exposures to market or industry risk.

Estimation window and out-of-sample design. Model estimation is conducted using a rolling window of 120 months. At each time t, the MSRR problem is estimated using data from the preceding ten years, and the resulting parameters are applied to construct portfolio weights for month $t+1$. The out-of-sample evaluation period spans from February 2007 to June 2024, ensuring a sufficiently long horizon for performance assessment across different market environments.

Random feature generation and hyperparameters. The RFF construction introduces randomness through the sampling of ω_k . To ensure that results are not driven by a specific realization, we repeat the estimation process 20 times using different random seeds. For each seed, a new set of transformed features is generated, leading to a distinct model realization.

The scaling parameter γ is selected from the set $[0.5, 1, 2]$, with features evenly distributed across these values. This allows the model to capture patterns at different levels of smoothness. In addition, we consider a grid of ridge regularization parameters λ to control the stability of the MSRR solution. Performance is reported as an average across all combinations of random seeds and hyperparameter choices, ensuring that results are representative rather than driven by a specific configuration.

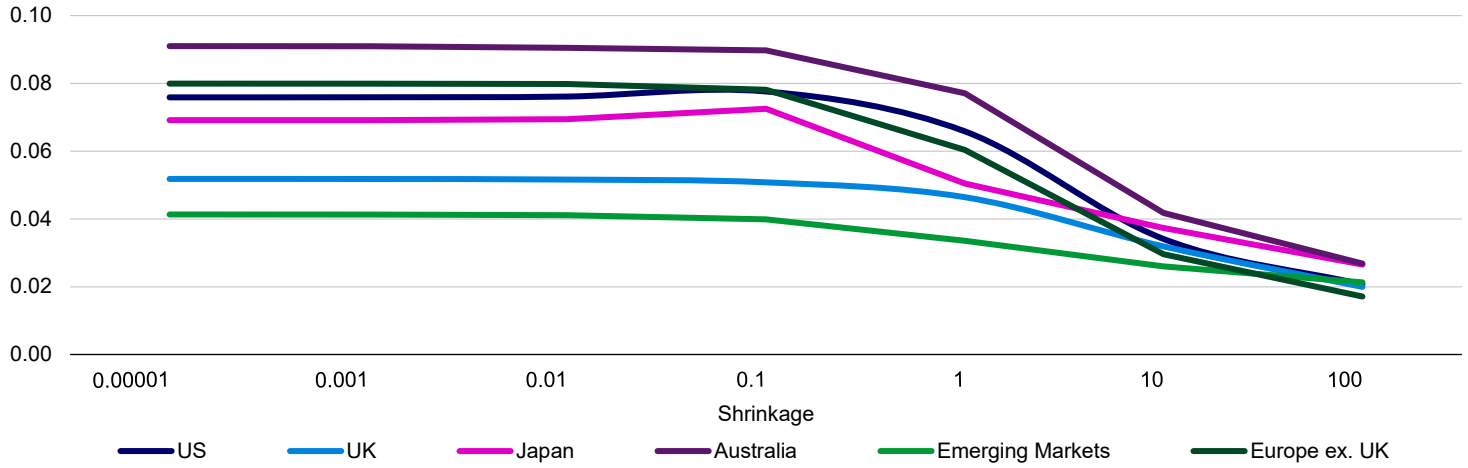
Portfolio construction and normalization. After estimating the factor weights via MSRR, asset-level portfolio weights are constructed using the feature representation. These weights are then adjusted to ensure comparability across models. Specifically, we apply market and industry neutralization by regressing the raw portfolio weights on market beta and industry dummy variables and using the residuals as final weights. This step removes systematic exposures that are not directly related to the underlying characteristics.

Finally, the portfolio is scaled to maintain unit leverage, with 100% long and 100% short exposure. This normalization ensures that performance comparisons across models are not driven by differences in gross exposure.

Turnover and transaction costs. Portfolio turnover is computed as the one-way change in portfolio weights across consecutive periods. Transaction costs are modeled as a linear function of turnover, with 25 basis points applied in developed markets and 50 basis points in emerging markets. These assumptions reflect differences in liquidity and market structure and are consistent with the empirical analysis in the main text.

Figure B.1: Standard deviation of AIPT Information Coefficients

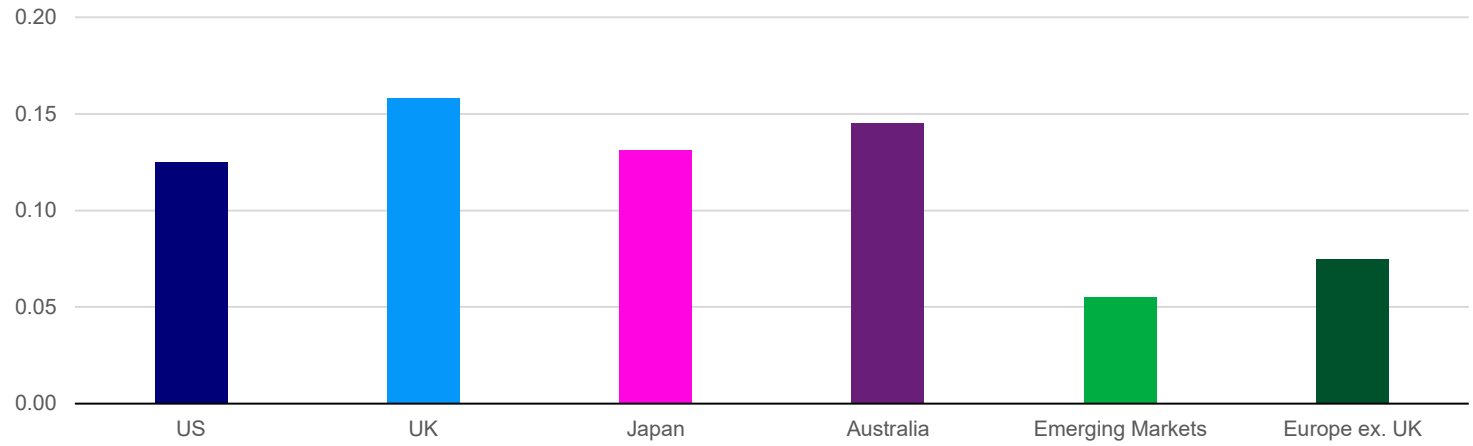
Plot of the standard deviation of gross Information Ratio (IR) across different seeds by shrinkage, from February 2007 to June 2024, across six major global equity regions. This figure illustrates the variability in gross IRs of AIPT multi-factor portfolios constructed using multiple random seeds and varying shrinkage strengths: $[10^{-5}, 10^{-3}, 10^{-2}, 10^{-1}, 1, 10, 10^{2}]$.



Source: Invesco. Simulated past performance is not a guarantee of future returns. All results are hypothetical and for academic illustration only.

Figure B.2: Standard deviation of AIPT Information Coefficients

Plot of the standard deviation of gross Information Ratio (IR) across different shrinkage parameters in various regions between February 2007 and June 2024. This figure illustrates the variability in gross IRs of AIPT multi-factor portfolios constructed across following ridge regularization shrinkage strengths: $[10^{-5}, 10^{-3}, 10^{-2}, 10^{-1}, 1, 10, 10^{2}]$.



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