Alternative Thinking 2024 Issue 2

Can Machines Time Markets?

The Virtue of Complexity in Return Prediction

Executive Summary

Machine learning techniques can be used to improve market timing strategies by picking up nonlinearities between the predictor variables (i.e., signals) and returns. In order to identify the nonlinearities, complex models, i.e., models where the number of predictor variables is larger than the number of return time series observations, must be estimated. More complex models better identify the true nonlinear relationships and, thus, produce better market timing strategy performance. This "virtue of complexity" result is validated in three practical market timing applications: timing the stock market, the bond market, and the long/short value factor. The performance improvements are real but modest, consistent with the view that machine learning applied to return prediction leads to evolutionary, not revolutionary, wealth gains.

PSG
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Contents

About the Portfolio Solutions Group

The Portfolio Solutions Group provides thought leadership to the broader investment community and custom analyses to help AQR clients achieve better portfolio outcomes.

AQR credits Jeff Cao, Pete Hecht, Bryan Kelly, and Nick McQuinn for their work on this paper. The lead authors thank Dan Heffernan, Antti Ilmanen, Thomas Maloney, and Dan Villalon for assistance and helpful comments.

Introduction and Framework

Machine learning techniques have flourished in environments with high predictability and large amounts of data. In general, larger, more complex models, i.e., models where the number of explanatory variables dramatically exceeds the number of dependent variable observations, have performed the best out-of-sample. This is confirmed by the accurate GPT-3 language model, which uses 175 billion parameters,[1] and various other image/natural language processing models which deploy astronomical parameterization in order to exactly fit the training data while also performing the best out-of-sample.[2]

In contrast to the environments described above, finance naturally has low predictability and small amounts of time series observations,[3] suggesting small, simple models—not complex machine learning models—are best suited for market timing applications.[4] However, new research is challenging this principle of parsimony.[5] Expected returns are likely nonlinear in the underlying predictor variables (i.e., signals), and small, simple market timing models miss this important relationship. Large, complex models are able to pick up the nonlinearities and produce better market timing performance. In fact, more complex models perform better out-of-sample—a so-called "virtue of complexity."

Exhibit 1: Degree of Predictability vs. Amount of Data

Source: AQR. For illustrative purposes only.

1 For example, when asked to predict the ending sentence of a five-sentence long story, GPT-3 was able to achieve over 80% accuracy. See Brown et al, (2020).
2 See Belkin (2021).
3 See Israel, Kelly, Moskowitz (2020) https://www.aqr.com/Insights/Research/Journal-Article/Can-Machines-Learn-Finance.
4 See Asness, Ilmanen, Maloney (2015) https://www.aqr.com/Insights/Research/Trade-Publication/Back-in-the-Hunt.
5 See Kelly, Malamud, and Zhou (2021).

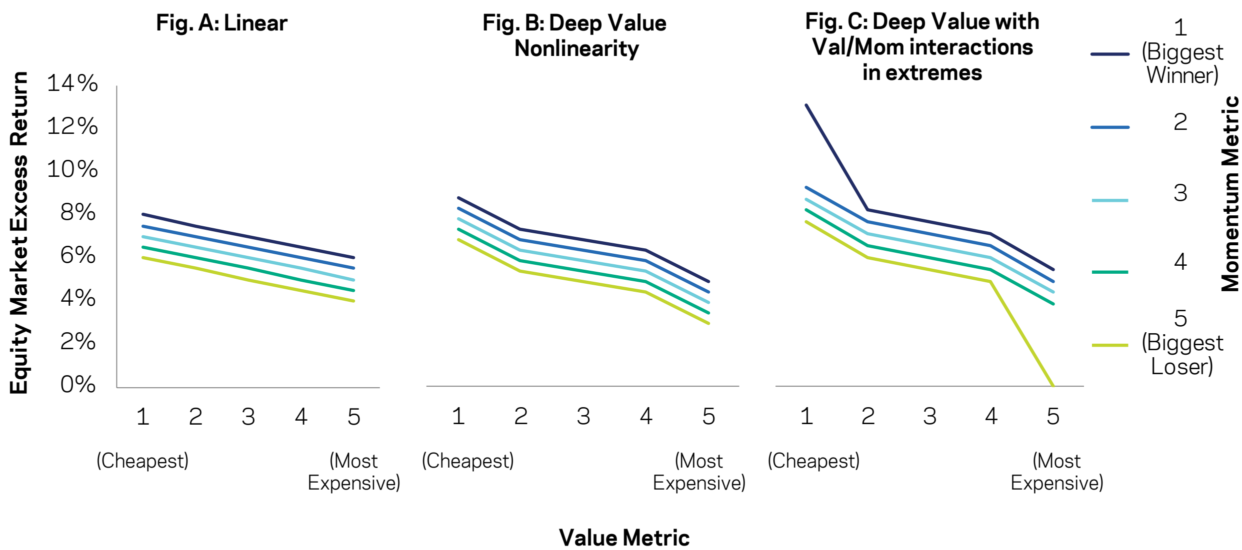
What Are Some Possible Nonlinearities in Expected Returns?

Let's start with a concrete return prediction example demonstrating how a simple linear model may differ from a more complex nonlinear one.

Assume expected returns are driven by two signals, valuations (i.e., value) and short-term performance (i.e., momentum). When valuations are low (i.e., cheap) and short-term performance has been good, expected returns are above average. **Exhibit 2 Figure A** depicts this relationship in a linear manner. But what if there is an additional expected return impact when valuations are at extremes—so called "deep value"?[6] This nonlinearity is highlighted in **Exhibit 2 Figure B**. Additional nonlinearities between the signals and returns can be incorporated, such as having an outsized return impact when extreme valuations and momentum are aligned, i.e. the market is extremely cheap with unusually high short-term performance (**Exhibit 2 Figure C**).

Exhibit 2: Nonlinearity Examples in Expected Equity Return

Hypothetical Equity Market Excess Returns



Source: AQR. Market returns, "value metric", and "momentum metric" data are hypothetical and for illustrative purposes only. The value metric is a generic example metric of valuation, and the momentum metric is a generic metric of short-term performance. Hypothetical data has certain inherent limitations, some of which are disclosed in the Appendix.

6 See Asness et al (2021) https://www.aqr.com/Insights/Research/Working-Paper/Deep-Value.

Why Do More Complex Models Perform Better?

Complex return prediction models better reflect reality by picking up nonlinearities between the signals (G) and future returns (R). In practice, the nonlinear relationships are unknown and must be estimated. This can be done by estimating a large, complex linear model where P new predictor variables (S) are generated by taking nonlinear transformations of the original signals (G). Refer to **Exhibit 3**.

Exhibit 3: A Complex Market Timing Model

True Model: $R_{t+1} = f(G_t) + \varepsilon_{t+1}$

Empirical Model: $R_{t+1} = \sum_{i=1}^{P} S_{i,t}\,\beta_i + \tilde{\varepsilon}_{t+1}$

where:
- S is a nonlinear function of G
- P is the number of model parameters

How many nonlinear transformations of the original signals should be used in the empirical model, i.e. should P be small or large? If we first focus on the market timing expected return objective, a more complex model with higher P would better approximate the true return prediction model. As a result, more complex market timing models with higher P deliver higher expected returns. This is consistent with **Exhibit 4**, which graphs the expected return from a market timing strategy as a function of model complexity (C). C equals the number of predictor variables in the model (P) divided by the number of time series observations (T). When C is less than one, we are in familiar statistical territory with more data (T) than predictor variables (P). Standard least squares regression can be used. When C is greater than one, there are an infinite number of solutions to the least-squares problem. As a result, we must employ regularization techniques, such as ridge regression, to estimate the expected return model. Ridge regression introduces bias via shrinkage into the expected return forecast.[7] Net-net, the expected return is increasing in complexity as the benefits of better true-model-approximation dominate the costs of rising bias from shrinkage.[8]

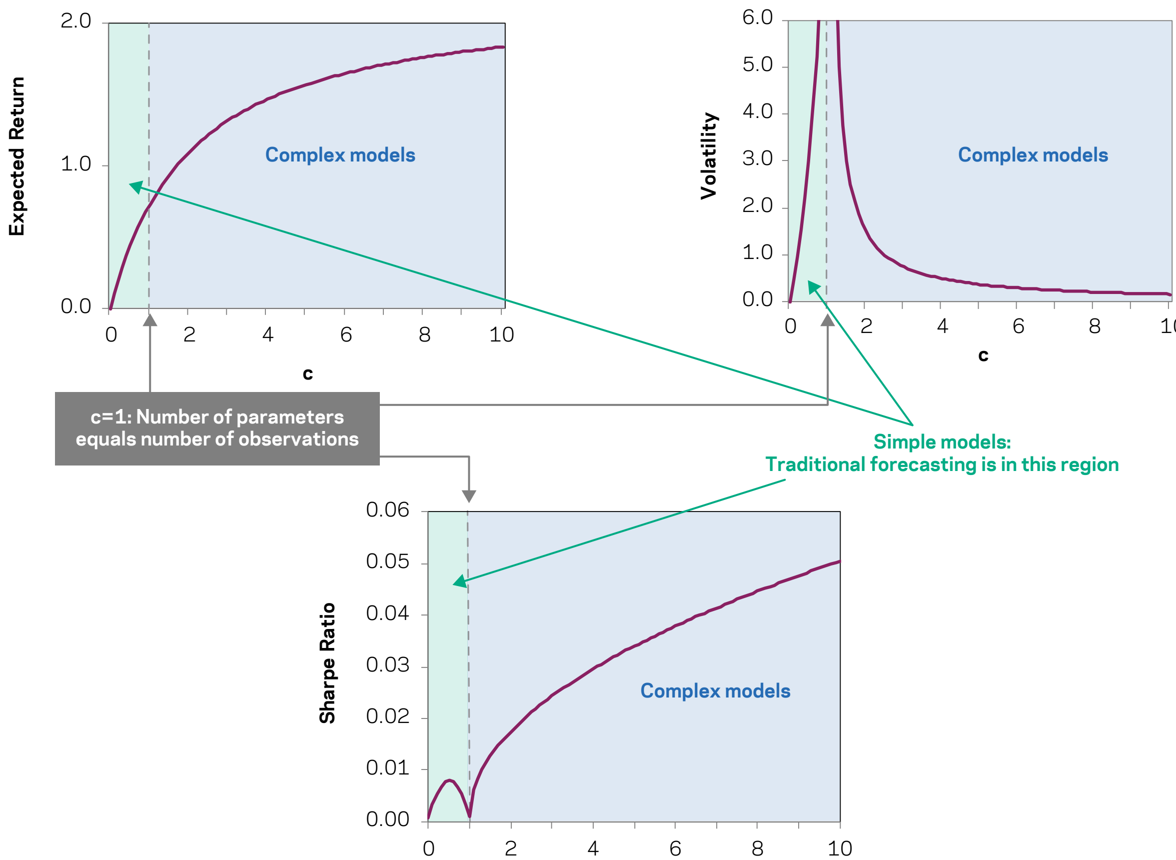
Market timing performance isn't just based on expected returns. Returns must be risk-adjusted. While it might be intuitive that more complex models deliver better expected returns, it's not obvious that they can do so with a reasonable amount of risk. Complex return prediction models—models with few data points and many parameters—could be very difficult to estimate, increasing the volatility of the market timing strategy. This phenomenon is observed in **Exhibit 4** when $C \leqslant 1$. As the number of predictor variables gets close to the number of time series observations, the betas of the model are

7 Ridge regression solves for the betas that minimize the following objective function: $\sum_{t=1}^{T}\left(y_t - \sum_{i=1}^{P} x_{t,i}\beta_i\right)^2 + \lambda\sum_{i=1}^{P}\beta_i^2$. Lambda penalizes large betas, shrinking the betas towards zero.

8 For more evidence, please see Kelly et al (2021).

estimated imprecisely and market timing volatility explodes. However, as model complexity increases, the regularization techniques of ridge regression are able to identify a set of betas that fit the data and can be estimated with high precision (i.e., small variance). As a result, the market timing Sharpe ratio is increasing in model complexity when C is greater than one—the so-called virtue of complexity applied to market timing.

Exhibit 4: The Trading Strategy Perspective of Complex Models



Source: AQR, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=517667. For illustrative purposes only.

Sounds Great in Theory, but Does It Work in Practice?

So far we have been focusing on the theory behind why more complex return prediction models deliver better market timing strategy performance. Let's now apply the theory to three practical market timing problems: timing the stock market, timing the bond market, and timing the long/short value factor. Can complex models time these markets and factors? Yes.

Timing the stock market

Our stock return prediction model uses the 15 macroeconomic and financial market signals studied by the famous Goyal and Welch return predictability paper (see **Exhibit 5**).[9] In order to identify nonlinear relationships between the signals and future returns, we estimate a 12-month rolling ridge regression with 12,000 predictor variables (i.e., a complexity C of 12,000/12 = 1,000). The US stock excess return from 1927 to 2020 is the dependent variable while the 12,000 predictor variables are generated by taking nonlinear combinations of the 15 raw Goyal-Welch (GW) signals.[10] Our market timing portfolio weight is equal to the forecasted return generated from the complex, 12-month rolling ridge regression.[11] When the forecasted return is positive, we go long, and when the forecasted return is negative, we go short.

We also construct a "simple" timing model which similarly goes long or short the forecasted return from a 12-month rolling linear regression of the market return on the original 15 *raw* GW predictor signals.[12]

The out-of-sample market timing performance using our complex model is reported in **Exhibit 5**. The strategy generates almost a 0.5 Sharpe ratio. Most of the performance can't be explained by static market exposure: the appraisal ratio (aka alpha Sharpe ratio) is over 0.3 with an alpha t-stat of almost 3. While the passive market is negatively skewed, the market timing strategy is positively skewed. In other words, the strategy generates attractive risk-adjusted returns without exposure to infrequent, large, left tail events.[13]

9 See Goyal and Welch (2008).
10 We generate 12,000 so-called random Fourier features from the 15 original variables. This process approximates a neural network.
11 This approximately maximizes the Sharpe ratio from the market timing strategy.
12 When the number of parameters exceeds observations, there are infinite solutions to the least squares regression objective. In order to identify a unique solution, we choose the minimizing solution for the linear regression with the smallest sum of squared betas. This is also known as "ridgeless" regression, or ridge regression where the shrinkage parameter approaches zero in the limit.
13 The results reported in the paper do not reflect the impact of transaction costs. Other AQR research has validated the virtue of complexity principle in an environment with transaction costs and other market frictions.

Exhibit 5: Hypothetical Out-of-Sample Equity Market Timing Performance using Goyal-Welch Predictors

January 1, 1927 – December 31, 2020

We use 15 predictor variables: default-yield spread, inflation, stock variance, dividend payout ratio, long-term gov bond yield, term spread, t-bill rate, pure credit return, dividend-price ratio, dividend yield, long-term gov bond return, earnings-price ratio, book-to-price, net equity expansion, and lagged market return.

The Sharpe ratio after adjusting for static market exposure

	US Stocks Excess Return	Simple Linear Timing Strategy Return	Complex Nonlinear Timing Strategy Return
Sharpe Ratio	0.51	-0.12	**0.47**
Appraisal Ratio		-0.19	**0.31**
Alpha t-stat		-1.74	**2.88**
Skew	-0.41	-1.29	**2.54**

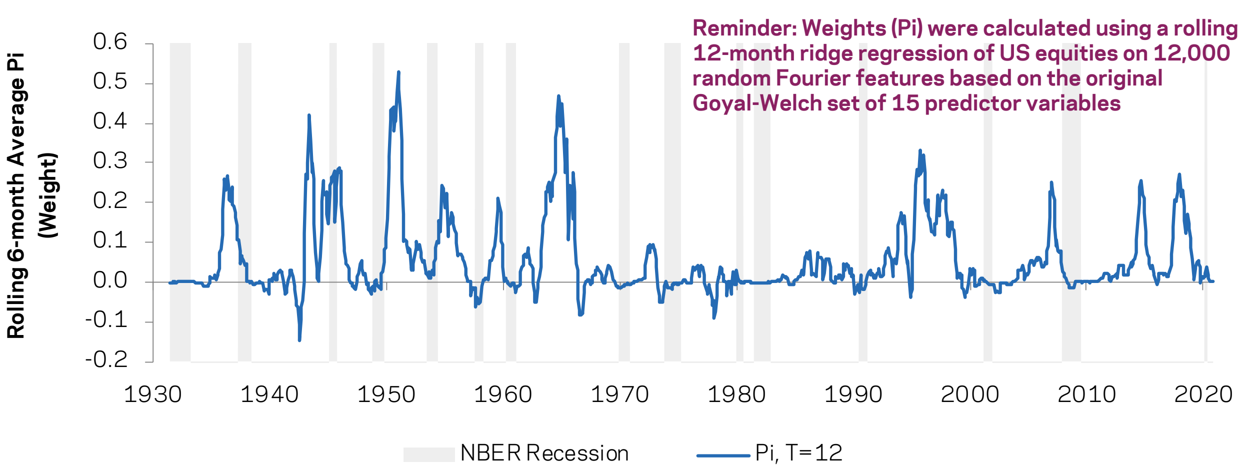
The untimed stock market has *negative* skew

Source: AQR. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=517667. The above complex results use T=12, P=12,000 and the variables do not have lookahead bias. The dependent variable is the excess return of the CRSP Value-Weighted Index of the S&P 500 Universe. The statistics reported are for static exposure to U.S. stock market return, the simple timing strategy, and the nonlinear timing strategy. For illustrative purposes only. Hypothetical data has certain inherent limitations, some of which are disclosed in the Appendix.

To provide more transparency into the complex market timing model, the market timing portfolio weights and NBER recessions are graphed in **Exhibit 6**. The market timing strategy is able to avoid 14 out of the 15 recessions. The one exception is the 8-month recession of 1945. It is interesting to point out that the strategy is effectively long only, going long in between recessions and approximately getting out of the market during recessions.

Exhibit 6: Hypothetical Rolling 6-Month Average Market Timing Weights using Goyal-Welch Predictors

January 1, 1927 – December 31, 2020



Source: AQR, NBER. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=517667. The above results use T=12, P=12,000 and the variables do not have lookahead bias. The rolling 6-month weights reported are of the nonlinear timed U.S. stock market strategy. Hypothetical data has certain inherent limitations, some of which are disclosed in the Appendix.

Timing the bond market

We repeat the exercise from the previous section with one change: the dependent variable is now the excess return on the 10-year US treasury bond. The out-of-sample bond market timing performance using our complex model is reported in **Exhibit 7**. Consistent with the equity market timing results, the strategy generates a Sharpe ratio of 0.3. None of the performance can be explained by static market exposure: the appraisal ratio is also 0.3 with an alpha t-stat of 2.4. The bond market timing strategy is also positively skewed.

Exhibit 7: Hypothetical Out-of-Sample Bond Market Timing

June 1, 1945 – December 31, 2020*

We use 15 predictor variables: default-yield spread, inflation, stock variance, dividend payout ratio, long-term gov bond yield, term spread, t-bill rate, pure credit return, dividend-price ratio, dividend yield, long-term gov bond return, earnings-price ratio, book-to-price, net equity expansion, and lagged market return.

	US 10Y Treasury Excess Return	Simple Linear Timing Strategy Return	Complex Nonlinear Timing Strategy Return
Sharpe Ratio	0.08	0.01	**0.27**
Appraisal Ratio		0.02	**0.27**
Alpha t-stat		0.18	**2.36**
Skew	0.08	-0.90	**9.50**

Reminder: We use the exact same process and underlying independent variables as in Exhibit 5, except our new dependent variable is 10-Year US Treasury excess returns*.

* The Treasury returns we use start in 1945.
Source: AQR, Global Financial Data. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=517667. The above complex results use T=12, P=12,000 and the variables do not have lookahead bias. The dependent variable is the excess return of the Global Financial Data US 10-Year Treasury Bond TR Index. Cash is the 3-month Treasury bill return. The statistics reported are for static exposure to U.S. bond market return, the simple timing strategy, and the nonlinear timing strategy. Hypothetical data has certain inherent limitations, some of which are disclosed in the Appendix.

Timing the long/short value factor

Lastly, we move from timing traditional risk premia to timing one of the most famous alternative risk premia, the Fama-French long/short value factor (i.e., HML). It's the exact same set up as the previous sections except HML is our dependent variable. The spirit of the HML results are similar to those found when timing the stock and bond market. The HML timing strategy generates a 0.4 Sharpe ratio and appraisal ratio with an alpha t-stat of 3.4 and positive skew (**Exhibit 8**).

Exhibit 8: Hypothetical Out-of-Sample Fama-French Value Factor Timing

January 1, 1927 – December 31, 2020

	Fama-French Value Factor Return	Simple Linear Timing Strategy Return	Complex Nonlinear Timing Strategy Return
Sharpe Ratio	0.33	0.03	**0.42**
Appraisal Ratio		0.04	**0.36**
Alpha t-stat		0.37	**3.37**
Skew	1.20	6.92	**4.11**

Reminder: We use the exact same process and underlying independent variables as in Exhibits 5 and 7, except our new dependent variable is the FF Value factor "HML".

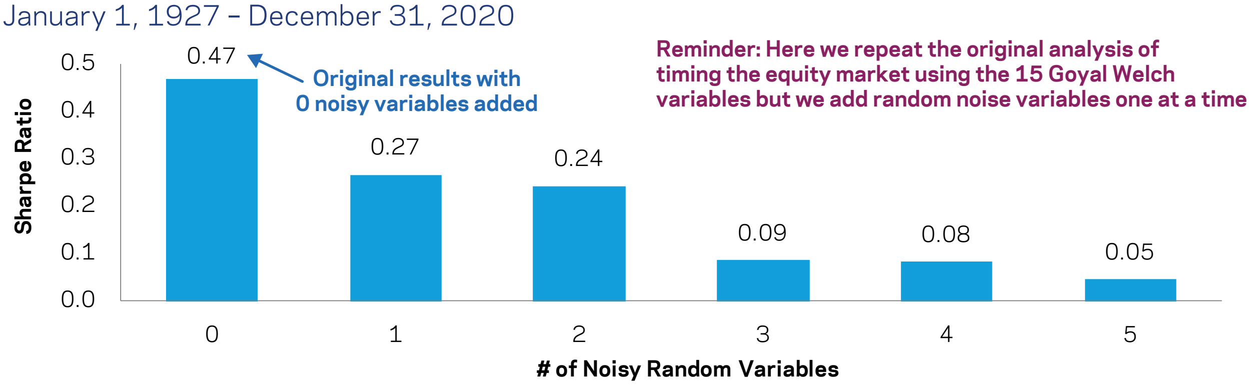
Source: AQR, Ken French Data Library. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=517667. The above complex results use T=12, P=12,000 and the variables do not have lookahead bias. The dependent variable is the Fama French US Value factor ("HML"). The statistics reported are for static exposure to U.S. HML return, the simple timing strategy, and the nonlinear timing strategy. Hypothetical data has certain inherent limitations, some of which are disclosed in the Appendix.

The Virtue of Complexity Is Not a License for Data Mining

Large, complex models can clearly help time various markets and long/short factors.[14] However, this virtue of complexity is not a license for throwing any predictor variable into the regression. It is critical that the underlying raw signals be related to the true nonlinear expected return model. Including signals with no relationship to the true expected return degrades market timing performance as seen in **Exhibit 9**. If we use the earlier complex stock return prediction model with the underlying 15 GW predictor variables, we achieve a market timing Sharpe ratio of 0.47. As we include noisy predictor variables alongside the original 15 GW variables, market timing strategy performance declines rapidly. Including just one noisy predictor variable reduces performance by almost 50%.

Exhibit 9: Hypothetical Out-of-Sample Equity Market Timing Performance adding Noise Variables to the 15 Goyal-Welch (2008) Variables

January 1, 1927 – December 31, 2020



Source: AQR. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=517667. The above results use T=12, P=12,000 and the variables do not have lookahead bias. The dependent variable is the excess return of the CRSP Value-Weighted Index of the S&P 500 Universe. The statistics reported are for the nonlinear timed U.S. stock market return with and without the addition of 1-5 standard normal random variables (in addition to the 15 Goyal-Welch predictor variables from the original study). Hypothetical data has certain inherent limitations, some of which are disclosed in the Appendix.

14 See Kelly et al (2022).

Concluding Thoughts and Future Research

Using small, simple return prediction models to market time misses nonlinear relationships between the predictor variables and future returns, leaving money on the table. Large, complex models overcome this limitation, better estimate the true expected return model, and generate better market timing performance—the so-called virtue of complexity. This virtue of complexity principle is validated in timing the stock market, bond market, and long/short value factor. The market timing Sharpe ratios adjusted for static exposure are in the neighborhood of 0.3. Thus, the performance improvements from implementing complex models are real but modest, consistent with the view that machine learning applied to return prediction leads to evolutionary, not revolutionary, wealth gains.

While this paper focuses on a time series, market timing application, the virtue of complexity also holds cross-sectionally when forming multi-factor portfolios.[15] For example, consider the following three popular stock selection factors: value, momentum, and low risk. What's the highest Sharpe ratio portfolio that can be constructed with these three factors, and can we materially improve upon this result by constructing additional factors which are nonlinear combinations of the original three signals? The answer to the latter question is yes—another cross-sectional variation of the virtue of complexity. Can machines build better multi-factor portfolios? Yes. More to come.

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15 See Didisheim et al (2023).

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The **Global Financial Data US 10-Year Bond TR Index** measures the return to constant-maturity 10-year US Treasury bonds.

The value factor **HML factor** follows Fama and French (1992, 1993 and 1996). It is the average return of the two value portfolios minus the return on the two growth portfolios. HML portfolios are value-weighted. The size and book-to-market breakpoints are refreshed in June of each calendar year, and the portfolios are rebalanced every calendar month to maintain value weights.

The **Goyal and Welch (2008) variables** are from "A Comprehensive Look at The Empirical Performance of Equity Premium Prediction" (Goyal and Welch, 2008). Please refer to Goyal and Welch (2008) for detailed descriptions of the variables.

Hypothetical Descriptions:

Hypothetical Out-of-Sample Market Timing Performances using Goyal-Welch Predictors (Exhibits 5, 7, 8)

The hypothetical out-of-sample marketing timing strategy uses 12-month rolling regressions of the market on 12,000, randomly generated nonlinear parameters to make monthly out-of-sample market return predictions. The dependent variable is the market return (equity market for Exhibit 5, bond market for Exhibit 7, and Fama-French Value Factor for Exhibit 8). We start by taking the 15 independent Goyal-Welch economic predictor variables and creating 12,000 nonlinear Fourier features (see Kelly et al, 2021), with gamma parameter of 4. We then run 12-month rolling ridge regressions with shrinkage parameter 1e3 of the market on the Goyal-Welch variables to calculate the next month's predicted return. We use to predicted return itself as the weight in the market return in each month to create market timing portfolio returns.

Hypothetical Rolling 6-Month Average Market Timing Weights using Goyal-Welch Predictors (Exhibit 6)

We plot the market return prediction (i.e., the timing strategy's weight in the market) from the regressions run in Exhibits 5 (US stock market) across time. These out-of-sample predictions/market timing weights are averaged on a rolling 6-month basis.

Hypothetical Out-of-Sample Equity Market Timing Performance adding K Noise Variables to the 15 Goyal-Welch (2008) Variables:

We perform the same analysis in the out-of-sample equity market timing strategy (Exhibit 5) using all full sample Goyal-Welch predictors, except we introduce randomly generated noise signals one at a time (until a maximum of 5 random noise signals). The random noise is sampled monthly from a standard normal distribution. The Sharpe ratios of these portfolios are shown.

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