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To Trade or Not to Trade? Informed Trading with Short-Term Signals for Long-Term Investors

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When long-term investors trade slowly changing portfolios, they are not particularly sensitive to when they should place or modify their bets. Short-term information can be used to guide investors on how to time their trades. Strategic trade modification provides exposure to short-term signals without imposing additional transaction costs or capacity limits. Long-term investors should not ignore short-term information simply because it is too expensive to trade on.

One of the great frustrations and disappointments in the asset management profession is to watch trading costs render useless a signal that predicts near-term returns beautifully. What is one to do with this predictive information? One option is to invest resources in hopes of refining the signal sufficiently to more than cover its trading costs—and then pray that the refined signal is not overfitted. Alternatively, the signal may be combined with additional unrelated short-term information to obtain sufficient predictability. Unfortunately, because both options are easier said than done, short-term signals are usually placed in the circular file.

Although ignoring short-term signals' predictive information is wasteful, the cost-to-benefit ratio of trading on such information may not appear to make sense at first glance—after all, paying $10 for $3 of *expected* revenues is not good business *if you try to trade on this information alone*. In this article, we offer an alternative algorithm that exploits rapidly decaying information without requiring the payment of additional transaction costs. The catch is that our algorithm works only in conjunction with another portfolio whose signals have slower information decay. Our algorithm provides an additional benefit for investors primarily focused on long-term portfolios: They can effectively get paid to take the short-term bet through the reduced transaction costs of trading the long-term portfolio.

When long-term investors trade slowly changing portfolios, they are not particularly sensitive to when they should place or modify their bets. The focus of our study was whether the value of the embedded optionality provided by this flexibility may be extracted by using short-term information to time the trade (i.e., exercise the option). The simplest algorithm is binary. If the short-term view concurs with the trade, then the trade is placed; otherwise, the investor waits for a more favorable environment. Delaying a trade has a cost because the information driving the long-term view also decays, albeit at a slower rate. If the short-term information provides superior forecasts of near-term returns, however, the delayed trade allows the investor to kill two birds with one stone by avoiding an expected short-term loss on the trade and reducing transaction costs. If there is any chance that the investor will change her mind on the trade over time, then delaying the trade reduces expected transaction costs by avoiding senseless round-trip trades. *Informed trading* increases the portfolio's exposure to short-term signals. Because trades that are consistent with the short-term forecast are allowed and those that are inconsistent are prohibited, the rebalanced informed-trading portfolio looks more like the short-term portfolio than it did before the trade. An investor who has information that the market will likely move against her trade in the near term avoids making an "error" and is effectively paid to do so.

Although these benefits can stand on their own and tilt the cost–benefit balance of collecting short-term information toward long-term investors, the informed-trading algorithm provides additional advantages. By strategically delaying certain trades, the informed-trading portfolio has lower expected trading costs than the original long-term portfolio for any given trading aggressiveness. The ability of informed trading to increase the portfolio's exposure to short-term signals is greater when

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trading aggressively. Together, these two properties suggest that trading the informed-trading portfolio more aggressively than the long-term portfolio is optimal. For instance, an investor who originally traded 2 percent toward his desired portfolio may find that trading 5 percent is optimal when using the informed-trading algorithm. This benefit is important because under traditional portfolio construction, an exposure to one signal may be increased only through an offsetting reduction of exposure to another signal. Informed trading can provide an exposure to a new signal while maintaining (or increasing) the portfolio's exposure to its original existing factors.

An important criticism of trading with short-term signals is that their capacity is limited.[1] Allocating a large amount of capital reduces the market inefficiencies that generate the short-term signal in the first place. This criticism, however, does not apply to our algorithm. Rather than trade on this information, we would avoid trading against it and thus deny other short-term traders the opportunity to profit at our expense. Mistake avoidance has no dollar capacity constraints. Of course, in equilibrium, if many investors avoid trading on the basis of a given signal, there will be fewer inefficiencies and the signal will weaken significantly, if not disappear altogether. But if the actions of other investors are held constant, one can benefit from short-term information through informed trading, whether one manages $10 million or $10 billion.

The literature on optimal portfolio rebalancing rules with transaction costs is extensive (see, e.g., Leland 1999; Buetow, Sellers, Trotter, Hunt, and Whipple 2002; Mulvey and Simsek 2002; Plaxco and Arnott 2002; Donohue and Yip 2003; Mitchell and Braun 2004; Sun, Fan, Chen, Schouwenaars, and Albota 2006). In aggregate, these studies demonstrate that the aggressiveness with which an asset should be traded is related to its trading cost and information decay.[2] In the study most similar to ours, Gârleanu and Pedersen (2010) set the gold standard by extending the literature with an optimal solution to the dynamic optimization problem whereby investors combine signals that have different levels of information decay (i.e., short- and long-term signals). Their solution provides the implied optimal weight for each signal and suggests how aggressively to trade during each rebalancing. To obtain their solution, trading costs are assumed to be quadratic so that the investor's objective function remains linear-quadratic. This assumption implies that for every signal, there is a profitable trade size with transaction costs small enough not to consume the alpha. With algorithmic trading of exchange-traded instruments, quadratic transaction costs may be a close approximation for some trades, but they are not the norm. OTC trades and even algorithmic trades often incur a minimum transaction cost. One can show that the solution to the dynamic optimization problem with a minimum fixed trading cost involves canceling some trades when the short-term signal and the change in the long-term signal are in conflict because the expected value of the trade is lower than the trading cost threshold.[3]

Our algorithm is in the spirit of that solution because it prohibits trades when this conflict arises. The parsimony of our algorithm requires little information about the term structure of expected returns. One set of factors is aggregated and designated the long-term signal, and another set of factors is aggregated and designated the short-term signal. Another distinction is that the optimal solution of Gârleanu and Pedersen (2010) requires significantly more information than our simplified approach does. To determine an optimum, one weighs the risk-adjusted performance of each signal against a quadratic trading cost while taking into account its information decay. Because our algorithm ignores these important properties, we do not provide the optimal portfolio. The binary trading rule, however, is likely subject to less specification error. As any practitioner can affirm, there is significant uncertainty about signals' expected risk-adjusted performance (what is the expected equity risk premium?) and assets' trading costs. Although the rate of signal information decay can be estimated more precisely, it is time varying, which means that it too may contribute to specification error. The potential misspecification issues aside, the goal of our study was to show that even a simple informed-trading algorithm that uses seemingly unprofitable short-term signals may enhance performance.

A Stylized Example

Let us begin with a stylized example of an informed-trading algorithm. This example provides intuition on how the informed-trading algorithm enhances performance. First, informed trading helps reduce portfolio losses by preventing trades that are inconsistent with the short-term outlook for an asset. Second, when there is a chance that long-term views will mean-revert, informed trading reduces unnecessary round-trip trades. Our relatively simple example involves two trades of a single asset in which the near-term returns are known.

Suppose that we currently hold 100 shares of an asset and would like to reduce our position to 50 shares owing to a moderated long-term outlook for the asset. Although our long-term outlook has been tempered, our short-term outlook is positive and we know with certainty that the asset's price will increase $1 a share over the next week. The one-way trading cost is $1 a share, which means that we cannot profitably trade on our short-term view because the round-trip trading cost is greater than the gross trading profit.

What should we do? We have two options:

1. *Trade immediately*. We may simply ignore our short-term outlook and proceed with the 50-share liquidation. If we do so, we realize a profit on our remaining 50-share position.
2. *Delay the trade.* Using the short-term outlook to inform our trade timing, we sell the desired 50 shares at the end of the week and profit on 100 shares. At the end of the week, we have the same position as in the option to trade immediately.

Although this exposition shows how we may improve gross performance through informed trading, it does not show how the informed-trading algorithm reduces trading costs. If we are going to end up owning 50 shares no matter what happens, then informed trading simply delays the payment of the trading costs. Informed trading may also reduce transaction costs because desired allocations change over time. With that in mind, let us continue our example.

Suppose that at the end of the week, our long-term outlook changes again and we want to own 60 shares of the asset. If we have chosen the option to trade immediately, we would purchase 10 shares at the end of the week. Effectively, at the beginning of the week, we oversold 10 shares and thus have 20 shares of excessive trading. Under the delay-the-trade approach, we simply sell 40 rather than 50 shares at the end of the week and end up at the same place. We have just avoided paying transaction costs on 20 shares of trading.

You might ask whether this transaction is a common occurrence. For two reasons, the answer is yes. First, unless a portfolio is fixed over time, its views exhibit mean reversion. Second, there is always uncertainty about whether future positions will go up or down. For informed trading to save on transaction costs, all you need is some probability that the next trade will be in the opposite direction of the current trade. When the trades are in the same direction, there are no savings. When back-to-back trades disagree, informed trading prevents unnecessary round-trip transactions.

Using our example, we can illustrate the full benefits of our algorithm, including the saving on round-trip transaction costs. **Figure 1** provides a graphic representation of this scenario, together with its total benefits. Assume a 50/50 probability that you want to hold either 50 or 70 shares at the end of the week. Under the trade-immediately approach, you either do nothing or purchase 20 shares at the end of the week, with equal probability. Under the delay-the-trade approach, you sell either 50 shares or 30 shares, with equal probability.

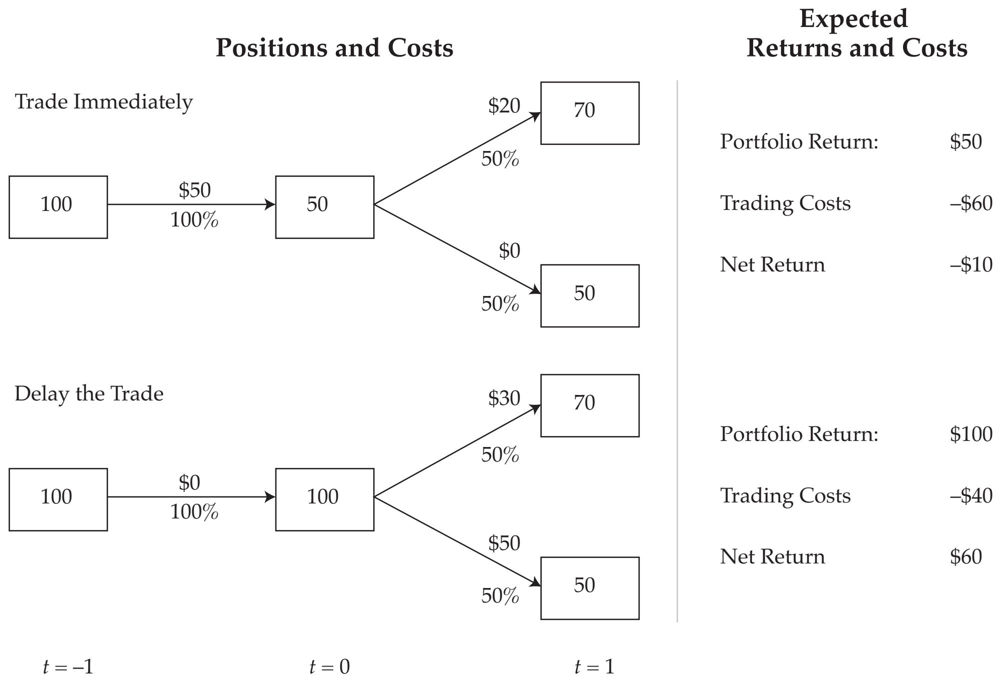
What are the total benefits? From a return perspective, the trade-immediately approach yields $50 ($1 a share on 50 shares) whereas the delay-the-trade approach yields $100. From a trading cost perspective, if we end up wanting to own 50 shares, both approaches lead to the same $50 in transaction costs, although the timing of the trades is different. If we want to own 70 shares at the end of the week, the trade-immediately approach pays $70 in trading costs ($50 for the first trade and $20 for the second), whereas the delay-the-trade approach pays $30 in trading costs. The total benefits of informed trading are a guaranteed $50 improvement by not selling before a capital gain and a 50 percent probability of reducing trading costs by $40. The total expected benefit is $70.

Regardless of the dynamics of the desired portfolio allocation, informed trading increases performance by preventing ill-timed trades. When there is a chance that the long-term view will mean-revert (a very likely condition), informed trading also improves net performance by reducing wasteful trades.

A Horse Race of Three Alternatives

We will horse race three approaches that a long-term portfolio manager can take with rapidly decaying information. The first approach is the base case, which we call the *long-term portfolio*, in which the portfolio manager simply ignores the short-term information and focuses entirely on the long-term objective. In the second case—the *mixed portfolio*—the short-term signal is treated as any other signal and the manager allocates to it some weight in the portfolio. The final case—the *informed-trading portfolio*, which we advocate in this article—uses the short-term information to time the portfolio's trades; specifically, we continue with a trade only if both signals agree on the direction of the trade and otherwise cancel it. For our horse race, we implement the informed-trading algorithm on a mixed portfolio. When creating the mixed portfolios for the second two horse race candidates, we select the signal weights that maximize net Sharpe ratios. The optimal mixture weights for the informed-trading portfolio may differ from those of the mixed portfolio.

Figure 1. Positions and Implied Costs Tree



Notes: This figure presents the positions of the stylized example using the traditional and informed-trading algorithms. The number of shares held at each point in time is provided in boxes: the starting position from the prior period, $t = -1$, the position selected by the respective algorithm at time $t = 0$, and the position selected by the respective algorithm at time $t = 1$. Transaction costs paid for the trades are reported above the arrows connecting the positions, and the probability of realizing the trade is reported below the arrow. The right-most column reports the expected returns and trading costs for the two rebalancings using the two algorithms.

By comparing the long-term portfolio with the mixed portfolio, we can determine whether short-term information can be profitably incorporated into a long-term portfolio by using traditional methods. We can then test whether informed trading adds more value by comparing its net performance with that of the mixed portfolio.

Constructing the Mixed Portfolio. The mixed portfolio combines two portfolios: a portfolio based on the long-term signal and a portfolio based on the short-term signal. Specifically, if $\mathbf{s}_{lt}$ is a long-term signal, standardized to be a Z-score, and $\mathbf{s}_{st}$ is a short-term signal, also standardized to be a Z-score, then we can define a mixed signal as $(1 - \delta)\mathbf{s}_{st} + \delta\mathbf{s}_{lt}$. We can form a portfolio on the basis of this signal after scaling it so that the long and short sides are each unit levered. The exposure to the short-term signal—and thus its effect on the performance of the portfolio—is defined by the parameter δ.

When full weight is placed on the short-term signal, the mixed portfolio's net Sharpe ratio is negative because the short-term signal is not profitable net of transaction costs. When full weight is placed on the long-term information, the mixed portfolio's net Sharpe ratio is positive because the signal is profitable net of trading costs. Because of diversification across the two signals and potential trade cancellation, the net Sharpe ratio does not have to decline monotonically as δ goes from 0 to 1. Thus, a δ between 0 and 1 may provide a higher net Sharpe ratio than that provided by the long-term portfolio. The δ that yields the highest net Sharpe ratio defines our *optimally mixed portfolio*. By construction, the optimally mixed portfolio's net performance is at least as good as that of the long-term portfolio because it may select a weight of 1 on the long-term signal and 0 on the short-term signal.

Trading Aggressiveness. We compare the net Sharpe ratios of the horse-raced portfolios as we adjust the level of trading aggressiveness. We define trading aggressiveness as how much we trade in the direction suggested by our new target portfolio from the currently held positions. As the optimal rebalancing literature shows, if a signal persists beyond a portfolio's rebalancing horizon or if proportional trading costs change with trade size—in the presence of transaction costs—fully trading to the desired portfolio is not optimal.

Trading aggressiveness, or trading speed, is the percentage of the difference between the current position and the desired position that is traded. For instance, if we are currently long 50 shares, would like to be long 150 shares, and have a 20 percent trading aggressiveness, then we would purchase 20 shares. On the next day, if we still want to be long 150 shares, then we purchase 16 additional shares. A similarly flavored approach is obtained by selecting the rebalancing frequency to slow down trading. Rebalancing daily is approximately five times more aggressive than rebalancing weekly. Many managers of long-term portfolios rebalance their portfolios at the end of each month.[4]

In our horse race, we independently select the trading aggressiveness for the long-term portfolio, the mixed portfolio, and the informed-trading portfolio that maximizes each one's respective net Sharpe ratio.[5] For the mixed and informed-trading portfolios, we select the optimal trading aggressiveness for each considered mixture weight and then select the mixture weight that maximizes their respective net Sharpe ratios. Hence, the long-term portfolio is optimized with respect to trading aggressiveness, and the mixed and informed-trading portfolios are optimized independently with respect to trading aggressiveness and signal weights. This approach provides the fairest comparison across the three alternatives.

Optimal trading aggressiveness is related to the rate of information decay. To capitalize on the signals' information content, short-term signals must be traded more aggressively than long-term signals. Therefore, we expect the mixed portfolio to trade more aggressively than the long-term portfolio and the informed-trading portfolio to trade more aggressively than the mixed portfolio.

Applying trading aggressiveness to our portfolios is a first-order approximation to portfolio optimization. A concern is that doing so is too naive. We may partly trade to a new view that a portfolio optimizer would have rejected because of transaction costs. We do not believe that this concern, though valid, meaningfully influences our results for two reasons. First, because the optimal trading aggressiveness at the daily frequency is very low (less than 4 percent for the long-term portfolio), only a small portion of the undesired trade is allowed to begin with. Further, that these trades would have been rejected by an optimizer indicates that their size is relatively small—the trades are rejected because the change in expected returns is small, and if the change in expected returns is small, then so too is the change in the desired portfolio positions. Second, our study compares multiple approaches to trading and each of the algorithms we horse race suffers from the same criticism: Trades that an optimizer would have rejected owing to transaction costs are allowed to take place. Although the mixed portfolio might benefit more, on the margin, from optimization than the informed-trading portfolio, we have found that this advantage is relatively small in practice.

Performance Metrics. In our horse race, the bottom line (i.e., the net Sharpe ratio) is what we ultimately care about. The net Sharpe ratio may improve because an algorithm successfully increases the *gross* Sharpe ratio, decreases trading costs, or both. For exposition, we report statistics on all three measures. Sharpe ratios capture the objective function of a mean–variance investor and are thus a good starting point for active investors. We ignore higher moments because they depend more on the underlying return characteristics of the optimal portfolio and less on the trading technique used to trade toward that portfolio.

We would also like to better understand what drives changes to the gross Sharpe ratio. On a gross basis, returns are driven by an exposure to the long-term signal, an exposure to the short-term signal, or both. If a portfolio's exposure to the short-term signal can be increased without doing too much damage to its exposure to the long-term signal, its gross performance should improve. To test this hypothesis, we estimate the following multivariate regression of the three candidate portfolios' returns on the long- and short-term portfolios that fully trade (trading aggressiveness = 1.0) to the desired positions because they represent the most up-to-date information the investor has:

$$r_{p,t} = \alpha + \beta_{lt} r_{lt,t} + \beta_{st} r_{st,t} + \varepsilon_{p,t},$$

where $r_{p,t}$, $r_{lt,t}$, and $r_{st,t}$ are returns on the horse-raced portfolio and the portfolios based on the long-term and short-term signals. This exposure is one of the most important properties of an investor's portfolio because, all else being equal, an investor should strive to maximize her portfolio's exposure to both long-term and short-term signals.

We next conduct two distinct sets of horse races. The first horse race—based on a simplified, but representative, real portfolio—reports the relative performances of the three alternatives in a realistic setting. The second focuses on a simulated sample, which facilitates a clear analysis of the mechanisms that drive the differences in performance between the alternative portfolios.

A Real Example

We will horse race the three alternatives on a basic, yet realistic, portfolio. We will test the three algorithms on a cross-sectional equity country index strategy across developed markets over 1 January 1990–31 December 2009.[6]

The long-term portfolio is designed to profit from the value and momentum anomalies. The value signal is formed by using book-to-price ratios, whereby countries with high book-to-price ratios are considered cheap (attractive) and countries with low book-to-price ratios are considered expensive (unattractive).[7] The momentum signal is the prior-one-year return (261 days), whereby high-return countries are expected to outperform low-return countries. The two signals are cross-sectionally standardized to obtain Z-scores. The final long-term portfolio averages the value and momentum Z-scores and rescales to obtain unit leverage on each of the long and short sides of the portfolio.[8]

The short-term portfolio is designed to profit from price reversals, which are often driven by a return to fair value after price moves caused by portfolio rebalancing or temporary market dislocations. Specifically, the signal is the negated one-week return (five days), whereby countries with low one-week returns are expected to outperform countries with high one-week returns. As with the long-term portfolio, the final short-term portfolio is based on a cross-sectionally standardized signal that is rescaled to obtain unit leverage.[9]

With the long- and short-term portfolios in hand, we can test the three alternative portfolios. The first two rows of **Table 1** report the performance, both gross and net of transaction costs, of all the portfolios that are fully traded to their desired positions (i.e., without respect to transaction costs). The long-term *value–momentum* portfolio provides a 0.6 gross Sharpe ratio, but half of that is lost to transaction costs. With a 1.0 gross Sharpe ratio, the short-term *reversal* portfolio has higher gross performance than the long-term portfolio, even though it is just a single factor. Transaction costs overwhelm the short-term portfolio (at almost 2.5 times the portfolio's returns) and bring its net Sharpe ratio down to –1.4. This result is not atypical for short-term signals, the focus of our study; many high-frequency signals seem attractive, often more so than long-term signals, if the transaction costs required to implement them are ignored. Optimally mixing the long- and short-term signals—with a 94 percent weight applied to the long-term signal—improves the long-term portfolio's net performance from 0.30 to 0.35. The 0.05 improvement to the net Sharpe ratio is delivered through a 0.07 increase in the gross Sharpe ratio and a 0.02 increase in risk-adjusted transaction costs. When trading fully, the informed-trading algorithm wins with a 0.75 gross Sharpe ratio and a 0.62 net Sharpe ratio. Informed trading is successful at both increasing gross performance (by 25 percent) and reducing trading costs (by 58 percent). The combined effect more than doubles the long-term portfolio's net performance.

"Where do I sign up?" you might ask. To be fair, the performance summary ignores the possibility of changing the trading aggressiveness. Trading completely to the newly desired portfolio significantly overstates the informed-trading algorithm's performance improvement. At its best, which occurs when trading only 0.6 percent toward the desired positions, the long-term portfolio's net

Table 1. Performance Summary: Developed Equity Country Selection, January 1980–December 2009

	Long Term	Short Term	Optimally Mixed	Informed Trading
Gross Sharpe: Full rebalancing	0.60	1.00	0.67	0.75
Net Sharpe: Full rebalancing	0.30	–1.43	0.35	0.62
Optimal rebalancing aggressiveness	0.6%	—	0.6%	3.4%
Gross Sharpe: Optimal rebalancing	0.62	—	0.62	0.65
Net Sharpe: Optimal rebalancing	0.61	—	0.61	0.63
Exposure to long-term portfolio	0.79	—	0.79	0.86
Exposure to short-term portfolio	0.04	—	0.04	0.05
Costs at optimal rebalancing	–0.01	—	–0.01	–0.02

Note: This table reports performance statistics for the uninformed-trading long-term portfolio, the uninformed-trading optimally mixed portfolio, and the informed-trading long-term portfolio with respect to developed equity country selection.

Sharpe ratio is 0.61, significantly higher than the 0.30 achieved when trading fully.[10] The optimally mixed portfolio at optimal trading aggressiveness is identical to the long-term portfolio, with no weight allocated to the short-term signal.[11]

Figure 2 plots the net Sharpe ratio for the mixed and informed-trading portfolios as a function of the weight applied to the long-term signal. We can see that net performance is maximized when allocating the short-term signal zero weight. Thus, at least for a simplified developed equity country selection model, the traditional approach to incorporating short-term return predictions is fruitless. Applying the informed-trading algorithm, however, improves both gross and net performance. The gross Sharpe ratio increases from 0.62 to 0.65, and the net Sharpe ratio goes from 0.61 to 0.63. Optimal trading aggressiveness increases from 0.6 percent to 3.4 percent. The increased trading aggressiveness provides a higher exposure to both the short-term and the long-term signals; the short-term exposure increases from 0.04 to 0.05 and the long-term exposure increases from 0.79 to 0.86. These benefits come at a price: The informed-trading algorithm pays approximately twice the trading costs of the long-term portfolio, which is not as high as one might think given that it trades nearly six times as aggressively as the long-term portfolio.

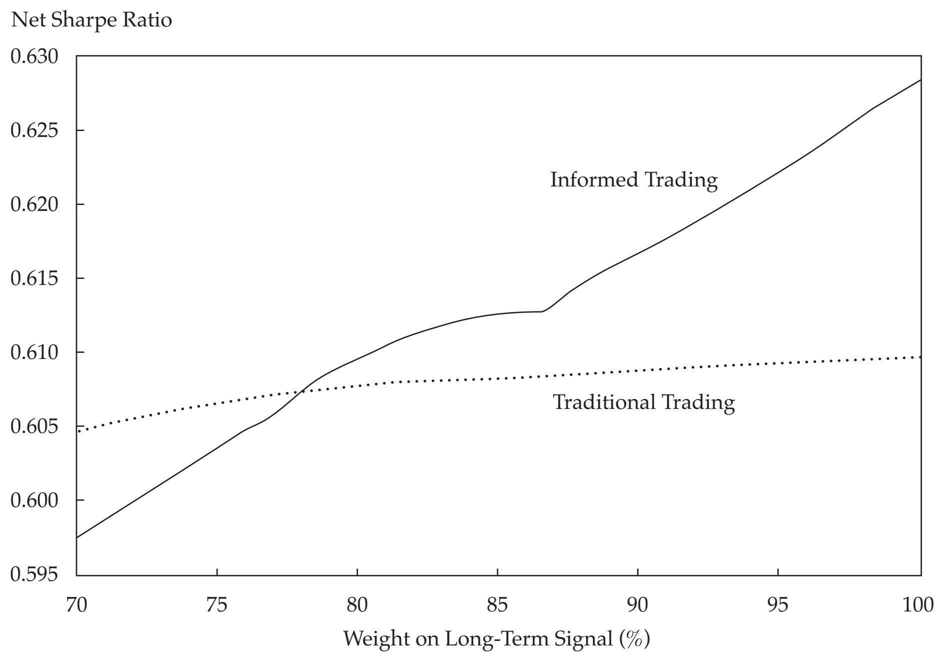
With respect to the realistic portfolio, the informed-trading algorithm provides better net performance than the two alternatives. It achieves this improved performance by increasing the exposure to the long-term signal while strategically picking how and when to introduce the exposure to the short-term signal. The additional costs incurred by rebalancing more frequently are more than offset by the enhanced gross performance.

A Simulated Example

We next horse race the alternative portfolios in a simulated example. Simulated portfolios help us avoid drawing conclusions on the basis of a specific sample with potential sampling error. Because of sampling error, a single realistic example is a very noisy reflection of the algorithm's expected performance. We thus use a parsimonious specification for the simulations that statistically mimics asset returns, return signals, and the portfolio allocation process.

Simulation Specification. In our example, we simulate three series for a group of assets: returns for each asset spanning multiple periods and two signals that predict these returns. The two signals differ in their predictive power and information decay

Figure 2. Mixed Portfolios' Net Performance: Developed Equity Country Selection



Note: This figure plots the net Sharpe ratio of the mixed portfolios under the traditional and informed-trading algorithms as a function of the signal weight applied to the long-term signal.

properties. The first signal is a long-term signal that decays slowly but predicts returns with a relatively low signal-to-noise ratio. The second signal is more predictive but decays quickly.

Specifically, we simulate 100,000 daily returns from the normal distribution for a universe consisting of 10 assets, each of which has 20 percent annualized return volatility and a 0.5 correlation with its peers. Our portfolios are dollar neutral (i.e., they have similar long and short sizes). As a result, the mean return of the assets is irrelevant and is left at zero.[12]

The returns are modeled by

$$\mathbf{r}_t = \frac{0.20}{\sqrt{261}} \boldsymbol{\Psi} \boldsymbol{\varepsilon}_t ,$$

where $t = 1 \ldots 100{,}000$, $\boldsymbol{\Psi}$ is the Cholesky decomposition of a correlation matrix in which all the off-diagonal terms are equal to 0.5, $\mathbf{r}_t$ is a 10×1 vector, and $\boldsymbol{\varepsilon}_t$ is a 10×1 vector drawn from the standard normal distribution. The returns are scaled to 20 percent annualized volatility.

To generate the two signals, we simulate two sets of 100,000 noise terms for each of the 10 assets from the normal distribution in the same way that returns are generated:

$$\mathbf{n}_{tj} = \boldsymbol{\Psi} \boldsymbol{\xi}_{tj} ,$$

where $t = 1 \ldots 100{,}000$, $j \in (slow, fast)$, $\boldsymbol{\xi}_{tj}$ is a 10×1 vector drawn from the standard normal distribution (separate draws for the slow and fast signals are uncorrelated to each other), and the noise terms have the same correlation structure as the simulated asset returns.

The signals are then formed as an exponentially weighted forward moving average of the return plus the noise:

$$\mathbf{s}_{tj} = \delta_j \mathbf{s}_{(t+1)j} + \left(1 - \delta_j\right)\left(\mathbf{r}_t + \gamma_j \mathbf{n}_{tj}\right),$$

where $\delta_{slow} = 260/261$ and $\delta_{fast} = 2/3$ are decay parameters and γ_j is a noise-to-signal parameter calibrated to achieve the desired Sharpe ratios for the two portfolios (0.75 for the long-term portfolio and 1.50 for the short-term portfolio). As γ_j increases, so too does the weight on the noise term, which causes the Sharpe ratio to decline. An exponential average is selected over a moving average so that we can obtain a more realistic alpha decay profile.[13]

The final portfolio vector, $\boldsymbol{\omega}_{tj}$, is generated by cross-sectionally demeaning $\mathbf{s}_{tj}$ and scaling so that both the long and the short sides of the portfolio have unit leverage. The portfolio return is $r_{tj}^p = \boldsymbol{\omega}_{tj}' \mathbf{r}_t$. We assume one-way transaction costs of 10 bps for estimating net performance statistics. We now have all the components we need to evaluate the performance of our simulated portfolios.

Performance Summary. Summarizing the performance of the alternative portfolios, **Table 2** is the simulated version of Table 1. By design, the short-term portfolio is untenable as a stand-alone signal. The informed-trading portfolio provides the highest gross and net performance of the three alternative portfolios, both when trading completely to the newly desired positions and when rebalancing optimally. With optimal rebalancing, the net Sharpe ratio of the informed-trading portfolio is 5 percent higher than that of the long-term portfolio and 2 percent higher than that of the optimally mixed portfolio.

The optimally mixed portfolio trades 32 percent more aggressively than the long-term portfolio. **Figure 3** plots the net Sharpe ratios of the mixed and informed-trading portfolios as a function of the

Table 2. Performance Summary: Simulations

	Long Term	Short Term	Optimally Mixed	Informed Trading
Gross Sharpe: Full rebalancing	0.75	1.50	0.80	0.86
Net Sharpe: Full rebalancing	0.32	–2.37	0.34	0.62
Optimal rebalancing aggressiveness	3.8%	—	5.0%	10.2%
Gross Sharpe: Optimal rebalancing	0.73	—	0.79	0.80
Net Sharpe: Optimal rebalancing	0.67	—	0.69	0.71
Exposure to long-term portfolio	0.90	—	0.89	0.92
Exposure to short-term portfolio	0.00	—	0.03	0.04
Costs at optimal rebalancing	–0.06	—	–0.10	–0.09

Note: This table reports performance statistics for the uninformed-trading long-term portfolio, the uninformed-trading optimally mixed portfolio, and the informed-trading long-term portfolio with respect to simulated portfolios.

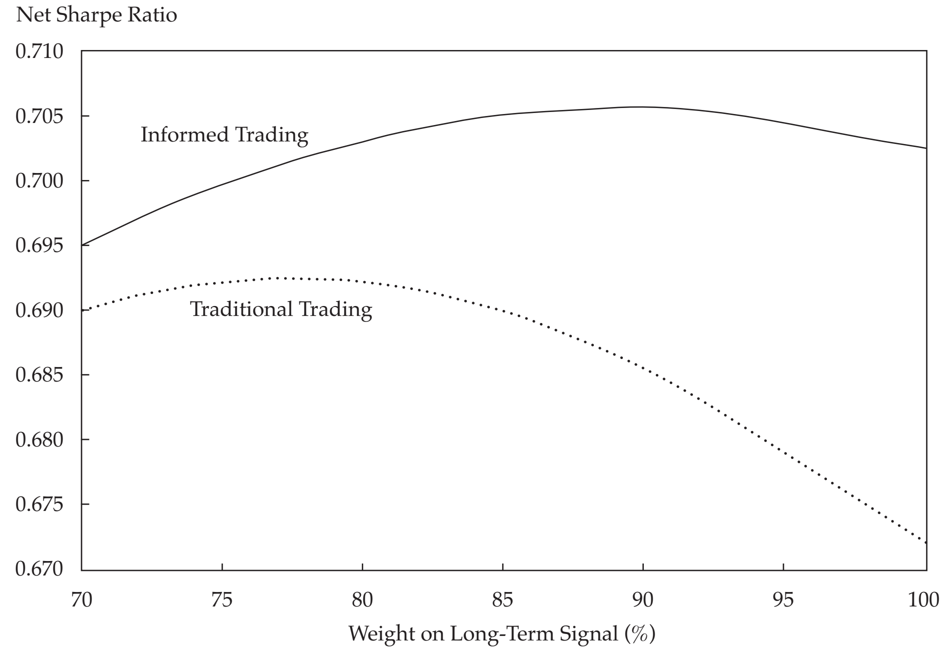
mixture weight applied to the long-term signal. We can see that the net performance of the mixed portfolio is maximized when a 22.5 percent weight is applied to the short-term signal. This result explains why it trades more aggressively than the long-term portfolio: so that it may benefit from the short-term information included in the final signal. Trading more aggressively to a portfolio that has a significant exposure to the short-term signal leads to higher trading costs—approximately 60 percent higher than those of the long-term portfolio. Yet, the mixed portfolio has a net Sharpe ratio of 0.69, an improvement over the 0.67 provided by the long-term portfolio. The mixed portfolio provides a 0.03 exposure to the short-term signal, as opposed to the long-term portfolio, which has none. The exposure to the long-term signal, however, is reduced slightly (from 0.90 to 0.89).

Looking again at Figure 3, we can see that the informed-trading portfolio also benefits by using a mixed signal for generating portfolio weights; its net performance is optimized when a 10 percent weight is applied to the short-term signal, less than half that desired by the mixed portfolio. Because of trade cancellation, however, the informed-trading algorithm trades twice as aggressively as the optimally mixed portfolio. In so doing, the informed-trading portfolio is able to achieve a higher exposure than the mixed portfolio to both the long-term portfolio and the short-term portfolio while paying lower trading costs. This win-win-win situation further improves the net Sharpe ratio to 0.71.

As mentioned earlier, if the exposure to the short-term signal can be increased without doing too much damage to the exposure to the long-term signal, gross performance should increase. **Figure 4** shows that this result is achievable through informed trading. The figure scatterplots the exposure to the long-term signal on the x-axis against the exposure to the short-term signal on the y-axis for both the mixed portfolio and the informed-trading portfolio for mixture weights on the long-term signal ranging from 0.7 to 1.0, in increments of 0.0025. Trading aggressiveness is selected to maximize the net Sharpe ratio for each mixture weight. The figure shows that for any given long-term exposure, the informed-trading algorithm provides a greater exposure to the short-term signal than that provided by trading a mixed portfolio. For any given long-term exposure, informed trading provides an exposure to the short-term signal that is approximately 0.02 higher.[14]

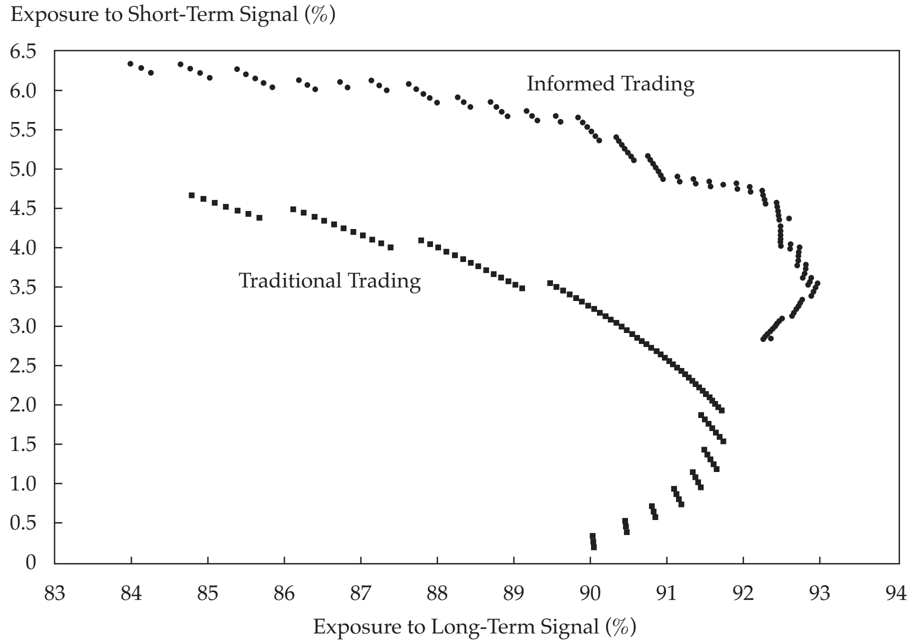
The exposures to the short-term signals are not obtained for free. **Figure 5** plots the risk-adjusted trading costs (gross Sharpe ratio minus net Sharpe ratio) against the exposure to the short-term signal for the mixed and informed-trading portfolios. Again, the points plotted in the figure are for mixture weights ranging between 0.7 and 1.0, in increments of 0.0025, and trading aggressiveness is selected to

Figure 3. Mixed Portfolios' Net Performance: Simulations



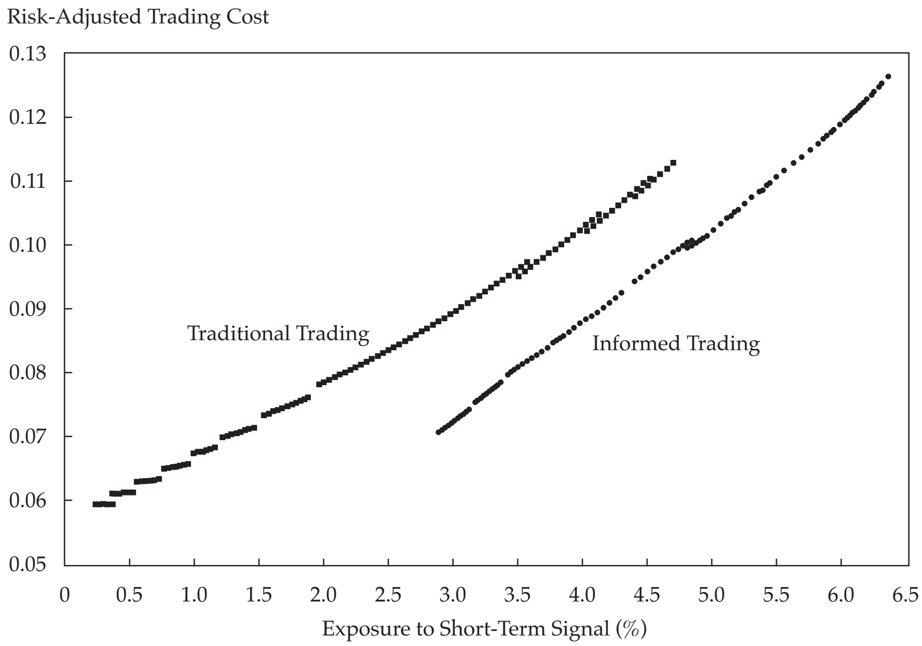
Note: This figure plots the net Sharpe ratio of the mixed portfolios under the traditional and informed-trading algorithms as a function of the signal weight applied to the long-term signal.

Figure 4. Exposures to Short- and Long-Term Signals: Simulations



Note: This figure plots the exposures of the mixed and informed-trading portfolios to the fully traded long- and short-term signals with respect to simulated portfolios.

Figure 5. Costs to Achieve Short-Term Exposure: Simulations



Note: This figure plots the risk-adjusted trading costs (gross Sharpe ratio minus net Sharpe ratio) of the mixed and informed-trading portfolios against the respective portfolios' exposures to the fully traded short-term signals with respect to simulated portfolios.

maximize the net Sharpe ratios. The figure shows that informed trading provides exposure to the short-term signal more cheaply than does traditionally trading the mixed portfolio. For instance, a 4.0 percent exposure to the short-term signal may be obtained for a 0.088 risk-adjusted trading cost with informed trading; the same exposure reduces the mixed portfolio's gross Sharpe ratio by 0.102.

Figures 4 and 5 show that (1) informed trading provides a higher exposure to the short-term signal for a given exposure to the long-term signal than does traditionally trading a mixed portfolio and (2) informed trading provides an exposure to the short-term signal more cheaply than does traditionally trading a mixed portfolio. Optimizing informed trading by carefully selecting the mixture weights on the two signals and trading aggressiveness balances three desirable properties: (1) exposure to the long-term signal, (2) exposure to the short-term signal, and (3) lower trading costs. In our simulated example, the informed-trading portfolio is more attractive than the mixed portfolio on all three dimensions, although that may not always be the case.

Influence of One-Way Trading Costs on Performance. For our analysis, we have assumed one-way trading costs of 10 bps, a reasonable (if not conservative) estimate if trading international equity futures but an unreasonably optimistic estimate if trading a large cross section of U.S. stocks. One might well ask how that assumption affects our results.[15] **Table 3** reports the net Sharpe ratios and portfolio exposures to the short-term signal for the three horse-raced portfolios as we vary one-way trading costs from 10 bps to 100 bps.

Not surprisingly, as trading costs increase, net Sharpe ratios decline for all three candidate portfolios. The optimally mixed portfolio always outperforms the long-term portfolio, albeit at a declining rate as trading costs increase. The convergence is expected because when costs are higher, the optimal mixture weight on the short-term signal declines. Eventually, the costs are so high that no weight is placed on the short-term signal and the two portfolios are identical. The informed-trading portfolio always outperforms the long-term and optimally mixed portfolios, but its edge also declines as trading costs increase. Again, as trading costs become increasingly high, the informed-trading portfolio will choose a mixture weight approaching 1 on the long-term portfolio. The informed-trading portfolio, however, continues to benefit from its cancellation of undesirable trades (from the perspective of the short-term signal).

Panel B of Table 3 provides additional evidence. The optimally mixed portfolio's exposure to the short-term signal converges to that of the long-term portfolio. The informed-trading portfolio's exposure to the short-term signal declines as trading costs increase but remains higher than that of the two alternatives. Informed trading continues to cancel undesirable trades; but as trading costs increase, the optimal mixture weight on both the short-term signal and trading aggressiveness declines. As trading costs increase, an optimizing portfolio manager will adjust his portfolio less. Eventually, the portfolio is adjusted far too slowly and the trades become far too small to benefit meaningfully from trade timing.

Table 3. One-Way Trading Costs and Performance: Simulations

Trading Costs	Long Term	Optimally Mixed	Informed Trading
A. Net Sharpe ratios			
10 bps	0.672	0.692	0.706
20	0.620	0.627	0.645
30	0.577	0.581	0.599
40	0.540	0.542	0.559
50	0.506	0.508	0.523
60	0.475	0.476	0.490
70	0.447	0.448	0.460
80	0.420	0.420	0.431
90	0.395	0.395	0.405
100	0.371	0.372	0.379
B. Exposure to short-term signal			
10 bps	0.002	0.035	0.041
20	0.003	0.012	0.022
30	0.004	0.009	0.019
40	0.004	0.007	0.018
50	0.004	0.007	0.017
60	0.004	0.006	0.016
70	0.005	0.006	0.015
80	0.005	0.006	0.014
90	0.005	0.005	0.013
100	0.005	0.005	0.013

Note: This table reports performance statistics for the uninformed-trading long-term portfolio, the uninformed-trading optimally mixed portfolio, and the informed-trading long-term portfolio with respect to simulated portfolios.

How Meaningful Is the Performance Improvement?

In our test case for developed equity country selection, informed trading improves net performance by 3 percent, increasing the net Sharpe ratio from 0.61 for the long-term stand-alone portfolio to 0.63 for the informed-trading portfolio. In the simulated environment, the increase in the net Sharpe ratio is larger, going from 0.67 for the long-term portfolio to 0.71 for the informed-trading portfolio, an improvement of 5 percent. With respect to the optimally mixed portfolio, the improvement is around 3 percent in both cases. At first glance, this result may seem relatively insignificant. Should we really be excited about an improvement to net performance of 5 percent?

Not surprisingly, we say yes. For a portfolio that maintains a 15 percent annualized volatility target (comparable to the S&P 500 Index), the informed-trading portfolio earns 50 bps a year more than the traditional trading approach. On a stand-alone basis, the 50 bp improvement is large enough, in our opinion, to justify the effort. Yet, a firm has limited research resources. Perhaps those resources would be better invested in improving the performance of the long-term portfolio. For a mature and well-developed strategy, we are not confident that a focus on additional long-term factors is a better resource allocation; increasing net performance by 5 percent is no easy task. The 0.75 long-term simulated gross Sharpe ratio may be obtained by mixing 10 *orthogonal* signals, each of which has a 0.24 gross Sharpe ratio. An improvement of 5 percent would effectively require adding an 11th orthogonal signal with the same 0.24 gross Sharpe ratio. Because the low-hanging fruit has likely already been picked, we are not confident that finding that 11th orthogonal signal is an easier task than finding a new untapped short-term signal that does not even need to be strong enough to pay for its own trading costs. For context, the S&P 500 provided a 0.23 gross Sharpe ratio between January 1965 and December 2009. From a resource allocation perspective, we believe that research on informed trading makes sense.

Short-Term Thinking for Long-Term Investors

For a portfolio manager who focuses on long-term strategies, the suggestion of developing and implementing high-turnover signals may be a tough sell. A manager of long-term portfolios may not be equipped to handle—or at least may have no comparative advantage in handling—the implementation details associated with high-frequency trading. Long-term investors who hear "high frequency" may tune out because it is seemingly irrelevant.

Not surprisingly, we argue that short-term thinking is worth long-term investors' time. We are not advocating that long-term investors trade high-frequency signals. Our suggestion is to use short-term information for trade modification, for which most high-frequency implementation issues are irrelevant. By choosing to delay a trade, substantial transaction costs may be avoided. A long-term investor may think that avoiding transaction costs is not important: If you rebalance only once or twice a quarter, why should you care?

Chances are, the reason a manager of long-horizon portfolios rebalances infrequently is an implicit or explicit trading cost optimization that determined more aggressive trading is unjustifiable. One should remember, however, that there is a trade-off: the trading cost versus the tracking error to the desired portfolio. By trading *smartly* through an informed-trading algorithm, the cost–benefit curve can be moved, more frequent (or aggressive) rebalancing becomes optimal, and the portfolio maintains lower tracking error to the underlying view. In addition to reduced tracking error, the portfolio picks up some exposure to a desirable short-term view. Put another way, some of the portfolio's tracking error to the long-term desired view is desirable because it is an exposure to a high-Sharpe-ratio short-term strategy.

One reason that long-term investors might ignore profitable high-frequency signals is the signals' limited capacity. The impact of a high-frequency signal on a large portfolio might be too small to justify the search cost because the risk allocation to the signal will be minuscule under capacity considerations. The informed-trading algorithm, however, does not actively trade on the high-frequency signal; it prevents trades that are inconsistent with it. Thus, for a given investor, high-frequency information can be used without capacity constraints. If all investors start using the same signal to delay trading, they will change the profitability of that signal in equilibrium and the signal will disappear. So long as one has any relevant information that the market has not fully incorporated into prices, however, the capacity for using that signal is unlimited. In our study, we considered short-term signals that do not cover transaction costs and emphasized that our algorithm allows an investor to use those signals. The benefits of using our algorithm are not restricted to signals that are not profitably tradable. Of course, an investor is free to inform trading with signals that cover transaction costs. What is important is that the signals are better predictors of near-term returns than is the new long-term information. Because capacity constraints are irrelevant, trading on the signal directly and avoiding trading against the signal are not mutually exclusive. An investor with a long-term horizon can thus deploy significantly more capital to express her short-term view.

Conclusion

Profitably trading high-turnover signals is a challenge. Gross performance must be impressive to cover trading costs and leave enough return to justify the operation. Even if performance is sufficient to pay for trading costs, capacity is usually constrained. You can put only so much money behind a signal before you have arbitraged it away.

In this article, we have offered an informed-trading algorithm that bypasses both issues for investors in longer-term portfolios. By allowing a short-term view to inform trading decisions on a long-term portfolio, investors can lower their portfolios' tracking error to its desired long-term view *and* obtain an exposure to an attractive short-term signal. High-frequency signals that do not cover their own trading costs become profitable and have no capacity constraints. Instead of trading the view, investors can simply make sure they never trade against the view.

The next time someone asks you, "Does this signal cover its trading costs?" or "What is the capacity of this short-term strategy?" you can honestly say, "It does not matter so long as the short-term information more accurately forecasts near-term returns than does the change in the long-term signal." Perhaps you can dust off some of the short-term factors you threw away because they were too expensive to trade. To finally profit from short-term signals that had long seemed unprofitable to implement can be quite satisfying. Happy hunting.

We would like to give special thanks to Cliff Asness and John Liew for their support and insights. Cliff has long advocated the use of high-frequency information to inform trading. We would also like to thank Brian Hurst, Lars Nielsen, Lasse Pedersen, Ashwin Thapar, and Otto Van Hemert for useful comments on this article. The information set forth herein has been obtained or derived from sources believed by the authors to be reliable. However, the authors do not make any representation or warranty, express or implied, as to the information's accuracy or completeness, nor do the authors recommend that the attached information serve as the basis of any investment decision. This document has been provided to you solely for information purposes and does not constitute an offer or solicitation of an offer, or any advice or recommendation, to purchase any securities or other financial instruments, and may not be construed as such.

This article qualifies for 1 CE credit.

Notes

1. See Kearns, Kulesza, and Nevmyvaka (2010) for an interesting study of high-frequency-signal capacity.
2. For the sake of parsimony, we applied the same level of trading aggressiveness to each asset in our portfolio. An improved approach would apply optimal rebalancing rules to determine the long-term portfolio as a first step in the rebalancing, followed by informed trading. In practice, we found that our overall results are robust to more advanced portfolio optimization techniques.
3. This result follows the no-trade region under proportional trading costs described by Leland (1999).
4. A number of studies have considered the choice of rebalancing frequency, both fixed and dynamic, in this context (see, e.g., Plaxco and Arnott 2002; Buetow et al. 2002; Donohue and Yip 2003; Sun et al. 2006).
5. As mentioned previously, this trading is somewhat naive versus a portfolio optimizer that balances the improvement to risk-adjusted returns against trading costs. In our study, we focused on a simple implementation that allowed us to show the benefits of informed trading without the need to look at the impact of an optimizer on the realized portfolio. Informed trading can be incorporated into a portfolio optimization framework in a number of ways, but that is outside the scope of our study. Aside from reducing transaction costs, one may use an optimizer for several reasons (e.g., an optimizer helps determine appropriate substitutions in portfolios with trading, position, and exposure constraints and allows the varying of trading at the asset level instead of the portfolio level).
6. We considered a cross section of the following 18 developed countries: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States. The returns for Denmark, Norway, and Portugal were from swap contracts; we obtained the data from Thomson Reuters Datastream. We obtained the remaining 15 countries' return data (for futures positions) from Bloomberg.
7. We obtained the book-to-price ratios for the various countries' MSCI indices from Datastream.
8. For the value anomaly, see Fama and French (1992, 1996, 1998). For the momentum anomaly, see Jegadeesh and Titman (1993); Asness (1994); Rouwenhorst (1998); Hong and Stein (1999). Asness, Moskowitz, and Pedersen (2009) combined the value and momentum signals to predict long-term returns across a number of asset classes, including equity country selection.
9. For price reversals, see Thaler and De Bondt (1985, 1987).
10. In fact, the 0.61 net Sharpe ratio is even higher than the 0.60 gross Sharpe ratio obtained when fully trading to the desired positions. This strange result is an excellent example of why we also analyzed simulations: to circumvent some of the noise provided by a small sample.
11. This result further demonstrates why we decided to analyze simulations.
12. Although important, a difference in the mean return across assets will generate only a long-term bias for that asset and will not affect the results of this simulation. We can model it as two separate portfolios: one with average positions driven by differences in cross-sectional means and another that has no long-term bias. The second portfolio drives the trading, and we prefer to abstract from this difference in means.
13. The ability to forecast one-day returns decays exponentially with this specification. A rolling mean has a flat alpha decay profile (i.e., no decay) until the day the window closes, when all predictability is lost. Because the exponentially

weighted moving average is an expanding estimate with an infinite look-back period (*look-ahead* in our case), we added 5,000 days to the beginning of our simulation but did not use them when computing performance statistics.

14. The choppiness of the scatterplot can be attributed to the discreteness of the two-way optimization. We optimized on a grid in which mixture weights ranged from 0.7 to 1.0 (in increments of 0.0025) on the long-term signal and trading aggressiveness ranged from 0.002 to 0.200 (in increments of 0.002). Because of the computational intensity of the informed-trading algorithm, we chose not to decrease the granularity any further.
15. We thank an anonymous referee for asking this important question.

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