Taking the Stag out of Stagflation

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ABSTRACT

In this paper we study investigate whether we can time the performance of stock market factors in a profitable manner. In the first part of our paper, we study a trading strategy that buys factors based on a timing strategy. We find that the factor timing strategy experiences lower maximum than our factor portfolio benchmark but does not produce the returns necessary, net of trading costs and 2% management and 20% performance fees, to outperform our factor benchmark. Additionally, the factor timing portfolio plays a very small role in an optimal portfolio that is comprised of a factor timing portfolio and our factor portfolio benchmark. In the second part of our paper, we test whether economic indicators can predict factor timing performance, net of the factor timing benchmark. We find that stagflation (a period of high inflation during a recession) is predictive of the outperformance of our factor timing strategy relative to our benchmark. We form a strategy that engages in factor timing and shorts our factor benchmark the month after a stagflation period is predicted and only buys our factor benchmark during all other times. We find that this strategy produces a Sharpe ratio of 1 and is negatively correlated to both stocks and bonds. We interpret this result as a discovery of a point of market inefficiency.

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Market timing has been an affinity of market participants. The urge for practitioners to implement new and different systems to mitigate market risks and drawdowns in order to avert the pain of loss has existed for hundreds of years. The simplest version of these phenomena is the well discussed tendency of investors to look at past returns and extrapolate these returns into the future. Jegadesh and Titman (1992) As a result large increases in asset prices, particularly those of stocks, have resulted in great frenzies. The earliest of these stock rises was the 17th century rise of the Dutch East India Trading Company and inspired the South Sea Bubble of 1720 and The Mississippi Bubble. In each of these events, investors looked at past returns and extrapolated the fortunes that they might have one day.

Today we call this technique trend following. It is a technique upon which an entire industry has been built. The modern seeds of this industry which follows trends in stocks were planted around the early 1970's with the advent of the trend following funds, and grew into modern funds that trend-follow stock market indices. Around the same time finance academics studied stock returns and concluded that the vast majority of stock returns could be explained by Factors, long-short portfolios of stocks that were sorted into certain categories according to their ranking based on certain characteristics. Factor investing became a popular strategy, alongside trend-following. Recently, a debate has emerged about whether factors themselves can be timed, in order to yield certain qualities such as excess returns, lower volatility, or lower maximum drawdowns.

Our investment technique uses trend following to time entries and exits into and from equity factors. Factor timing is a concept that has been studied with conflicting conclusions. Gupta and Kelly (2019) use a factor scaling technique that measures a set of lagged return z-scores against factor returns and conclude that factor timing is driven by common factors rather than stock specific idiosyncratic factors. Arnott, et al. (2019) study how past industry returns impact future industry returns and conclude that factor timing is most predictable at a one month time horizon and that factor timing can be captured by trading almost any set of factors. Factor timing techniques have also been implemented in practice by various asset managers.

In this paper, we test whether we can time the performance of factors by introducing a variation of the trend following strategy that is documented in Hurst, Ooi, and Pedersen (2017) and apply this strategy to all of the factors mentioned in Frazzini and Pedersen (2010). We find that factor timing based on trend following is not an effective strategy if we take transaction costs into account when looking at the factor timing's information ratio, when the strategy is benchmarked against its base factor. However, when we condition our results on economic indicators, we find that we can time factor returns. We gather our data from AQR's Data Library, specifically the Betting Against Beta Daily dataset. The contents of the dataset include data regarding the Market, Betting against Beta, Small minus Big, High minus Low, Up minus Down, High minus low devil, and risk free rate data for developed countries dating back until 1927.

We conclude that factor timing returns significantly outperform the returns of their benchmark factor returns on a risk adjusted basis- gross of transaction costs. After transaction costs have been removed from the factor timing returns, the risk adjusted performance of the factor timing strategy is insignificantly different from the base factor. When we condition the use of our strategy on a stagflation indicator, we find that our strategy outperforms a portfolio of equal weighted factors after transaction costs, 2% management fees and 20% performance fees.

Data

We use data from AQR's Data library to conduct this study. Our Data set contains data from a variety of countries with each respective country's data set having a different length of observations than others; starting dates for datasets can begin as early as 1927 and as late as 1998. We will use the data from 1998 to 2019 so that every country's results will be based on the same length of data.

Our dataset is limited to 1998 to 2019 and does not encompass data prior to 1998. This limits our ability to understand how the strategy performed in the cross section of countries through past major crises. Though our data set is limited in time, it is vast in breath of countries and allows us to test our theories on a global scale. We omitted our US data from 1927 to 1998 and our global data from 1985 to 1998. These omissions allow us to test our results on samples that have not been studied by Fama and French (1992).

We sourced our factor data used in from AQR's data library. Our data includes the daily factor returns for the following countries: Australia, Austria, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, Great Britain, Greece, Hong Kong, Ireland, Israel, Italy, Japan, The Netherlands, Norway, New Zealand, Portugal, Sweden, and The United States of America. Additionally, portfolios of the previously mentioned countries are also studied including a Global Portfolio, Global excluding the United States of America, Europe, Pacific, and North America.

The following factors are studied: Market, Betting against Beta, Small minus Big, High minus Low, Up minus Down, and High minus low devil for each respective country. The Market factor is the daily returns of a market weighted portfolio of all of the stocks in the specified country. Betting against Beta is the daily returns of a market weighted portfolio of long stocks that are in the bottom half of stocks that are ranked by their 3 year beta to their respective market portfolio and a market weighted portfolio of short stocks that are in the top half of stocks that are ranked by their 3 year beta to their respective market portfolio. Small minus Big factor is the daily returns of a market weighted portfolio of long stocks that are in the bottom half of stocks that are ranked by their market capitalization and a market weighted portfolio of short stocks that are in the top half of stocks that are ranked by their market capitalization. High minus Low factor is the daily returns of a market weighted portfolio of long stocks that are in the bottom half of stocks that are ranked by their book to market value at year-end and a market weighted portfolio of short stocks that are in the top half of stocks that are ranked by their book to market value at year-end. Up minus down factor is the daily returns of a market weighted portfolio of long stocks that are in the top half of stocks that are ranked by their twelve month stock return and a market weighted portfolio of short stocks that are in the bottom half of stocks that are ranked by their twelve month stock return. High minus Low devil factor is the daily returns of a market weighted portfolio of long stocks that are in the bottom half of stocks that are ranked by their book to market value during the prior day and a market weighted portfolio of short stocks that are in the top half of stocks that are ranked by their book to market value during the prior day.

Constructing the time series momentum strategy

Our factor trend following indicator buys a factor every time that there are two or more positive time horizons. Our factor trend following indicator sells a factor every time that there are two or more negative time horizons. We used this approach because it is the most similar to Hurst, Ooi, and Pedersen (2017)'s approach to trend following. We decided to replace the one month time horizon indicator with a three month time horizon indicator because we believe this is a better fit for stock returns.

Our strategy is devised by measuring adding the signs of the three months, six months, and one year indicators for each respective factor in each country. We then build a portfolio of these positions and equal weight each component in the portfolio. Our strategy is a long flat strategy which may not hold any factors at a given time.

In order to test practical applicability, we incorporate transaction costs into the returns of each factor at every point that the factors position changes from long to flat and flat to long. At said point, we deduct a 20 basis point transaction fee in order to account for the real world slippage that a large institutional portfolio would incur based on Frazzini, Israel, and Moskowitz (2018).

Performance over a Century

Exhibit 1 shows the return performance over various sets of periods and shows returns before and after costs and fees in addition to showing the volatility Sharpe ratio and correlation to equities and 10 year bonds for this portfolio.

Exhibit 1

Performance of Factor Timing, 1999-2019

Time Period	Return Gross of fee	Return Net of fee	Returns Net of 2/20 Fee, Net of Cost	Realized Volatility	Sharpe Ratio	Correlation with S&P	Correlation with Equal Weighted Factor Portfolio	Correlation with 10-year US Treasury Bond
1999-2000	5.3%	3.6%	1.4%	9.7%	0.14	-0.09	0.63	-0.06
2001-2005	18.2%	14.6%	9.0%	5.0%	1.78	-0.38	0.82	-0.28
2006-2010	8.8%	5.0%	1.4%	5.7%	0.25	-0.25	0.56	-0.16
2011-2015	7.0%	4.2%	1.5%	2.2%	0.68	-0.10	0.46	-0.13
2015-2019	5.6%	1.8%	-0.8%	6.4%	-0.13	-0.16	0.62	-0.20
Full Sample	11.2%	7.2%	3.1%	6.8%	0.45	-0.24	0.64	-0.13

Note: This exhibit shows the strategy's annualized excess returns (i.e., returns in excess f the risk-free interest rate), before and after simulated transaction costs, and gross and net of hypothetical 2-and-20 fees.

Net of transaction costs, the strategy has a Sharpe ratio of one which indicates that the strategy's returns are consistent across time for the measured sample. The strategy has traversed many large drawdowns; the period 2001 to 2005 which is displayed in Exhibit 1 shows an outsized return relative to other periods but, is also the period in which 5 of the 10 largest drawdowns were experienced. It appears that although the returns are consistent net of transaction costs, when we introduce a typical hedge fund fee structure of 2% management fees and 20% performance fees our returns over the full sample are reduced by more than 50%. Across or sample and in every period that is observed, our strategy net of management and transaction fees is negatively correlated with both US treasuries and the S&P 500. Our strategy also maintains an average correlation over the full sample of 63% to our equally weighted factor portfolio which serves as another benchmark.

Our strategy is profitable because it earns risk premium for a large number of drawdowns. When comparing Exhibit 1 to Exhibit 9, we see that there is a tradeoff between Sharpe ratio and maximum drawdown resulting in periods with high Sharpe ratio having a large number of drawdowns while periods with low Sharpe ratio having significantly less drawdowns due to fewer opportunities to earn risk premia for the frequency of drawdowns.

Exhibit 2 decomposes our indicator into smaller parts to see if the returns are consistent. Furthermore, it also examines the performance of a lagged version of the signal. It appears that the individual components of our strategy produce similar average returns (within 1-2%) of each other across our full sample. Lagging a signal allows us to discover whether our signal is robust to longer execution horizons. When we lag our signal by one month, we see that our performance only deteriorates by, on average, approximately 40 basis points.

Exhibit 2

Performance of Factor Timing Components, 1999-2019

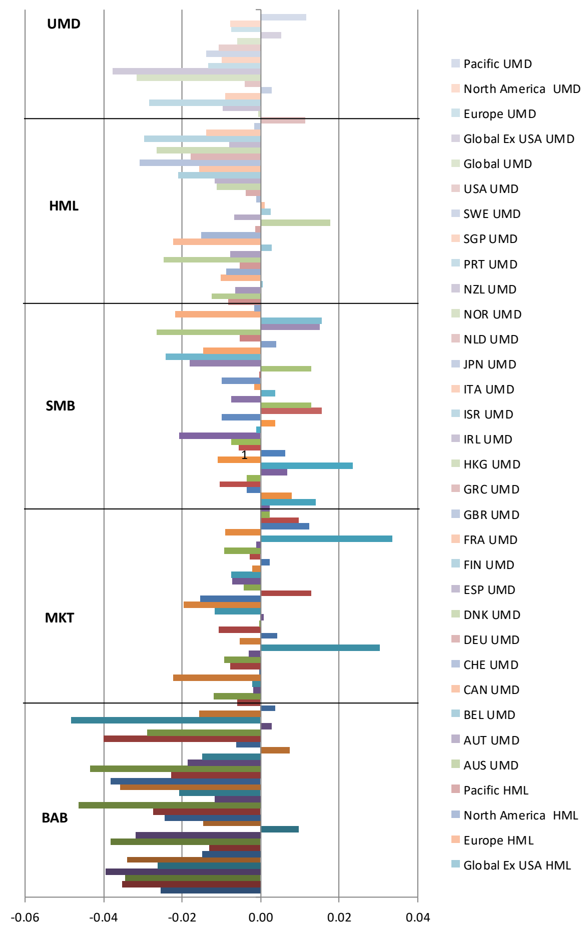
Time Period	3-mo strategy	3-mo lagged	6-mo strategy	6-mo lagged	12-mo strategy	12-mo lagged
1999-2000	5.16%	3.03%	4.06%	3.88%	2.77%	2.37%
2001-2005	14.26%	13.70%	17.30%	16.64%	16.64%	16.74%
2006-2010	8.08%	9.06%	10.05%	7.76%	6.09%	5.76%
2011-2015	5.62%	5.66%	5.32%	4.82%	5.68%	6.49%
2015-2019	5.28%	5.63%	5.46%	6.47%	5.36%	5.80%
Full Sample	9.62%	9.28%	10.52%	9.87%	9.08%	9.24%

Note: This exhibit shows the annualized gross Sharpe ratio (i.e., excess return before simulated transaction costs and fees divided by volatility) seperately for each time-series momentum signal based on the past 3-month, 6-month, and 12-month trend, respectively. Also, the table shows the performance when each of these signals is lagged by one month.

Our results in **Exhibit 3** show, on average, when applying the strategy to individual factors, the strategy when applied to that factor underperforms it's respective factor's performance on a risk adjusted basis, over the same period of testing as all other exhibits. Specifically, we tested our strategy on the period from 1999-2019. We wanted to examine individual information ratios so as to determine whether an investment manager that tracks a single factor strategy can achieve improved risk adjusted returns on such a strategy. It appears that investment managers cannot time a factor portfolio well enough, using our strategy, after transaction costs to outperform an equally weighted constant factor portfolio. The average information ratio across individual strategies is -.01 [before transaction costs] and -.02 [after transaction costs].

Exhibit 3

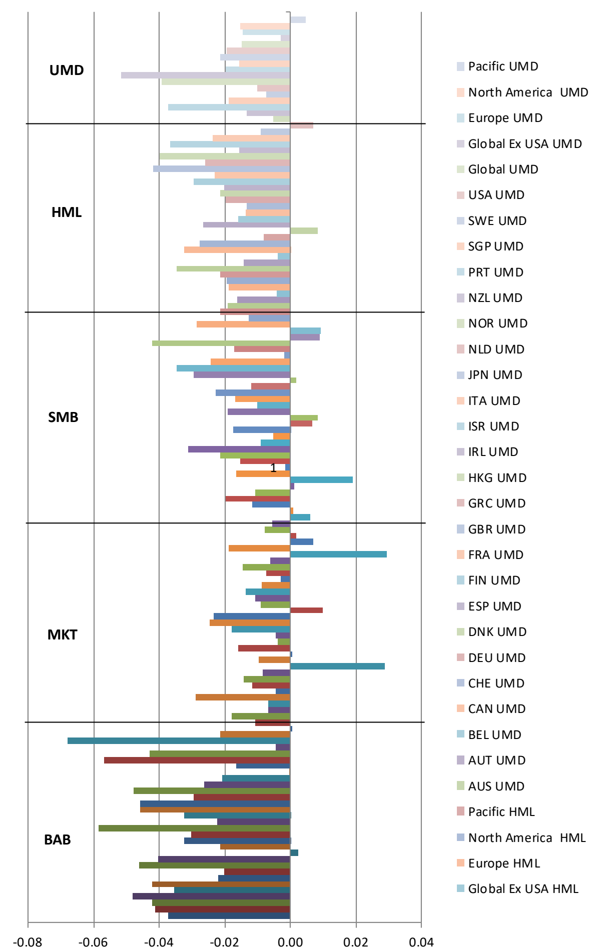
Factor Timing Information ratios vs their respective factors (gross of transaction costs)



Notes: This exhibit shows the Information ratio of factor timing (gross of fee, gross of cost) by factor

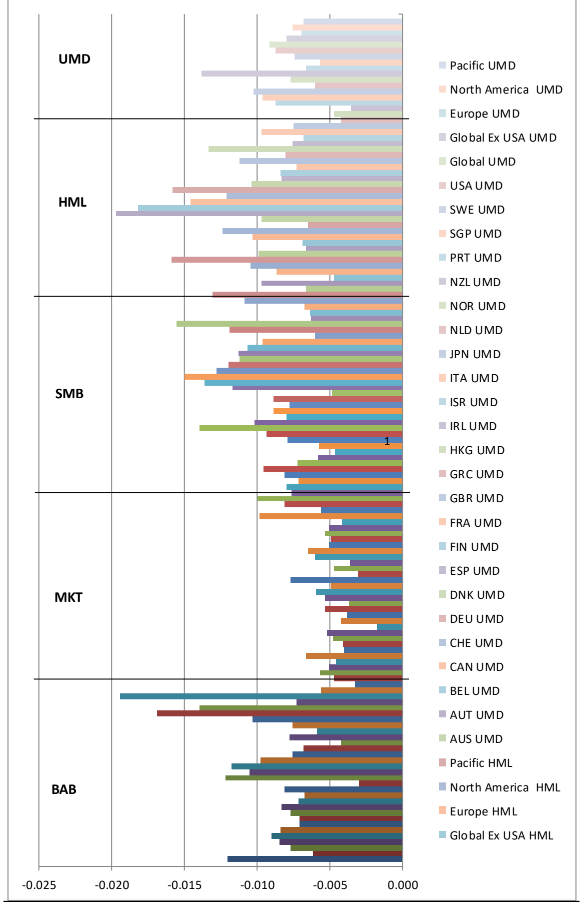
Our study is entirely out of sample because it replicates a similar paper which applied a version of our technique to trend following futures. Our study applies this technique to a completely different asset class and financial product type. Our study results exhibit similar characteristics of optionality in our respective return profiles. Our study echoes other empirical studies in identifying trend following returns as “crisis alpha”.

Exhibit 4A
Factor Timing Information ratios vs their respective factors (net of transaction costs)



Notes: This exhibit shows the Information ratio of factor timing (gross of fee, net of cost) by factor

Exhibit 4B
Transaction Costs impact on Factor timing strategy



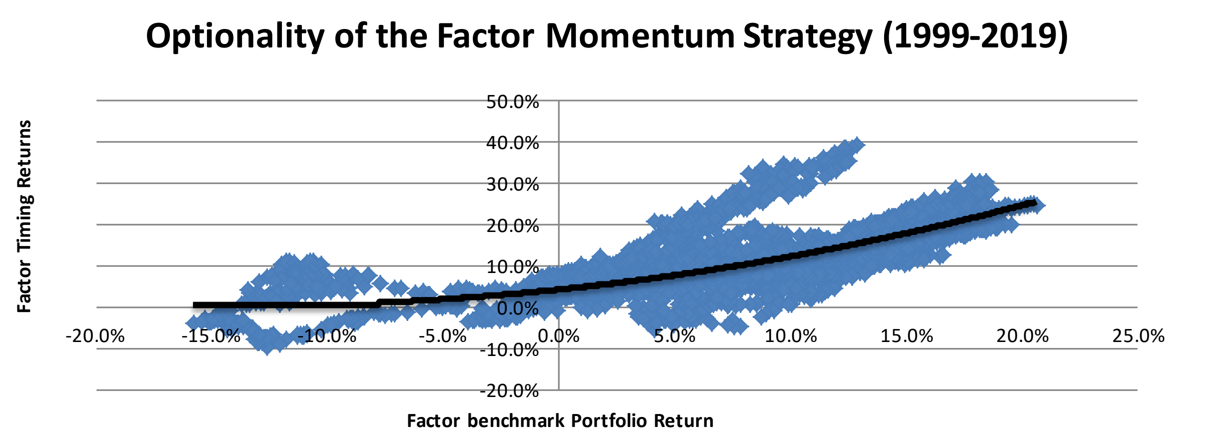
Notes: This exhibit shows the degredation of the Information ratio of factor timing due to transaction costs by factor

Performance During Crisis Periods

Our strategy exhibited unique characteristics when compared to stocks and bonds as well as futures. Our strategy, in our sample period, appears to be negatively correlated with both stocks and bonds. This occurred across every time period including our two post global financial crisis time periods. Our strategy performs in a similar fashion when compared to its underlying factors when those factors are appreciating but, our strategy does not exhibit the downside, on average, during the periods when factor returns are negative. **Exhibit 5** parts the returns our strategy on a year over

Exhibit 5

Factor Timing Optionality, 1999-2019



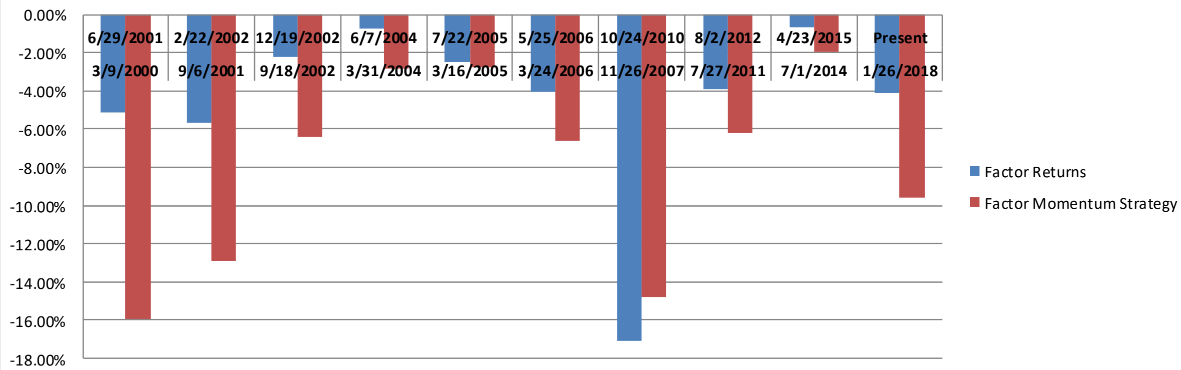
Note: This exhibit shows the annual returns of factor timing (gross of fee, net of cost) vs. factor portfolio, as well as the fitted second-order polynomial

year basis relative to its equal weighted factor benchmark. This plot agrees with the literature on trend following regarding its crisis alpha features and its ability to produce optionality in underlying return profiles.

While our factor portfolio is in drawdown, our factor timing strategy tends to underperform against the factor portfolio. **Exhibit 6** shows the performance of our factor timing strategy during the 10 largest drawdowns of the underlying factor portfolio. In nine out of the 10 largest drawdowns of our underlying factor portfolio, our strategy under performs the benchmark. What is unique about our strategy is that during the largest drawdown, our strategy experiences 2% less drawdown than our underlying factor portfolio. This agrees with our risk based theory of how factor timing leads to more frequent drawdowns but, has lower overall risks.

Theoretically, our factor is risk based and the rewards are based on the number of drawdowns in a period. This means that over a long-term horizon, the price has to appreciate in order for the strategy to participate in the underlying benchmark but, the strategy makes money based on the number of market shocks that occur. If a large drawdown were to happen, the strategy would not make any money because the signal would lower the exposure of the strategy to the underlying benchmark to zero. If there was excess demand for the strategy, the underlying benchmark would be pushed up but, as people are adjusting their positions based on the strategy, the sheer market impact of a large crowd that is selling based on the strategy would cause the strategy to lose money enough money to push out unsettled investors and decrease the risk premium during the time of crowding. The strategy's returns are based on the number of drawdowns and as such the returns of factor timing become convex due to transaction costs because more drawdowns will cause investors to need to

Exhibit 6 Factor Timing during the 10 worst drawdowns for factor returns



Note: This exhibit shows the returns of our factor timing strategy (gross of fee, net of cost) and return of our equally weighted factor portfolio over the 10 time periods selected as the largest drawdowns for the latter portfolio.

Exhibit 7

Combining an equally weighted factor portfolio with an allocation to Factor Timing, 1999-2018

	Annualized Excess of Cash Returns	Annualized Vol	Max Drawdown	Net of Fee Sharpe Ratio
Factor Portfolio	4.28%	6.88%	-17.41%	0.6220
80% Factor Portfolio 20% Factor Momentum Strategy	3.39%	6.53%	-16.62%	0.5188

Notes: This exhibit reports the historical performance of the equally weighted factor portfolio. Also, the table reports the performance of a portfolio with 80% invested in the equally weighted factor portfolio (gross of fees and transaction costs) and 20% invested in the factor timing strategy (net of fees and transaction costs).

get in and out of the strategy more frequently and trigger more transactions costs. As the number of drawdowns in the underlying index increase, the Sharpe ratio will also need to be not too high so that low volatility will cause a whipsaw affect that will create excess transaction costs but also not too low so that there is not enough return to pay for even the smallest of transaction costs.

The strategy net of 2% management fee and 20% performance fee is not a value add for its benchmark factor portfolio. **Exhibit 7** shows the impact of a 20% allocation to the factor timing portfolio and a 80% allocation to the benchmark factor portfolio versus the factor portfolio benchmark. The allocation to the factor timing portfolio decreases the maximum drawdown of the portfolio but also decreases the Sharpe ratio of the portfolio.

The stress periods are driven by the underlying factors themselves. **Exhibit 8** shows the 10 largest drawdowns in the amount of time the strategy took to realize and recover from each drawdown. We can see that the average Time from peak to trough is four months while the average time from trough to peak is also four months. When we compare **exhibit 8** to **Exhibit 6** we can see that the drawdowns of our underlying benchmark factor portfolio is highly correlated to the drawdowns of our factor timing strategy. We can conclude that the drawdowns from the underlying benchmark will affect the drawdowns from our factor timing strategy. The drawdown is calculated on a day-to-day basis and is measured as the deviation from the highest value of the per for you to that date.

Exhibit 8

The 10 Largest Drawdowns of our Factor Timing

Rank	Start of Drawdown	Trough of Drawdown	End of Drawdown	Size of Trough	Peak to through length (Months)	Through to Peak length (Months)
1	11/28/2008	7/23/2009	11/4/2010	-15.06%	8	4
2	2/1/2000	11/2/2000	3/14/2001	-15.62%	10	5
3	9/20/2001	1/18/2002	5/17/2002	-12.67%	4	4
4	10/3/2002	12/5/2002	3/10/2003	-9.75%	3	4
5	3/11/2003	4/23/2003	8/29/2003	-6.22%	2	5
6	12/15/2011	2/2/2012	5/14/2012	-6.15%	2	4
7	4/21/2006	7/19/2006	11/21/2006	-6.63%	3	5
8	1/9/2015	3/10/2015	6/16/2015	-4.67%	2	4
9	9/28/2015	11/4/2015	12/3/2015	-3.90%	2	1
10	1/1/2018	3/4/2019	Present	-9.51%	3	N/A

Note: This exhibit reports the 10 largest peak-to-through drawdowns of the Factor Timing, calculated using gross of fee, net of cost returns.

Performance across economic environments

We next consider The performance across different economic environment. This is interesting Post to understand the nature of the strategy and to further analyze its potential diversification benefits. Indeed, investors benefit most from strategies that deliver higher returns during tough times when their marginal utility of wealth is high we have already considered the performance during crisis. As defined by drawdowns in our benchmark factor portfolio, but several other economic environments are of interest.

Exhibit 9, panel A, considers the excess performance of the Factor timing portfolio over the benchmark factor portfolio across different regimes starting with the two classic macroeconomic characteristics or themes, growth and inflation. To analyze macro-economic growth, we separate the months into recessions and booms as defined by the NBER business cycle dating committee. We see that the performance is significantly different when comparing recession times to boom times. During recessions, the factor timing strategy outperforms the benchmark factor portfolio by 3% while during boom times the factor timing strategy underperforms the factor portfolio by -.83%. When looking at the t-statistics, both the out performance during recessions and the under performance during boom times are statistically significant. Next, the exhibit reports the performance across high versus low inflation environments, and, again we find similar out performance for factor timing during high inflation periods and under performance for factor timing during low inflation periods. The strong performance during high inflation and recessionary periods are evidence that the factor timing strategy provides returns that are negatively correlated to traditional investments.

Lastly, the table in **Exhibit 9**, Panel A, considers bull markets versus bear

Exhibit 9

Time-Series Momentum in Factors across Economic Regimes: Binary Indicators

Panel A: Time-Series Momentum in Factors Returns by Contemporaneous Macro Indicators

Macro Indicator	Statistic	Group 1	Group 2	Difference
Recession vs. Boom	Excess return	3.09%	-0.83%	0.00%
	(t-statistics)	5.09	-6.30	5.82
	Volatility	3.0%	4.0%	
	Sharpe Ratio	1.04	-0.21	
	% of occurances	11%	89%	
Inflation: High vs. Low	Excess return	2.66%	-3.25%	0.01%
	(t-statistics)	14.63	-18.24	16.45
	Volatility	1.4%	1.3%	
	Sharpe Ratio	1.85	-2.53	
	% of occurances	49%	51%	
Stock Market: Bull vs Bear	Excess return	-1.18%	1.29%	0%
	(t-statistics)	-15.14	3.60	-6.93
	Volatility	3.09%	4.05%	
	Sharpe Ratio	-0.38	0.32	
	% of occurances	69%	31%	

Panel B: Time-Series Momentum in Factors Returns by Lagged Contemporaneous Macro Indicators

Macro Indicator	Statistic	Group 1	Group 2	Difference
Recession vs. Boom	Excess return	1.3%	-0.6%	0.0%
	(t-statistics)	2.58	-4.43	3.74
	Volatility	3.2%	4.0%	
	Sharpe Ratio	0.11	0.89	
	% of occurances	11%	89%	
Inflation: High vs. Low	Excess return	2.20%	-2.84%	0.01%
	(t-statistics)	10.26	-11.84	14.16
	Volatility	1.5%	1.2%	
	Sharpe Ratio	1.44	-2.41	
	% of occurances	49%	51%	
Stock Market: Bull vs Bear	Excess return	-0.25%	-0.78%	0.00%
	(t-statistics)	-2.45	-1.51	0.23
	Volatility	2.99%	4.47%	
	Sharpe Ratio	-0.08	-0.17	
	% of occurances	68%	32%	

Notes: This exhibit shows the performance of the factor timing before fees and after simulated transaction costs. For each economic regime, we report the strategy's annualized excess return, its t-statistic, volatility, and Sharpe ratio. The regimes are "recession vs. boom" indicators as defined by NBER Business Cycle Dating Committee; "inflation: low vs. high" based on U.S. CPI from 1999 to 2019, based on Shiller [2000] who uses the Warren and Pearson [1935] price index; "stock market: bull vs. bear," where bear markets are defined as periods where the 200-day moving average is above the current price of the S&P 500 and bull market is all other times. In Panel A, we consider the contempouraneous effect while in Panel B we lag the indicator of the economic environment.

markets; Bear markets are defined as periods in which the S&P 500 drops below its 200 day moving average And ball markets are all other times. The Strategy has underperformed in bull markets and outperformed in bear markets, but the difference is only marginally significant, and perhaps a more robust result is the option curve in Exhibit 5.

Exhibit 9, panel B, considers the same economic environment, but now the economic environment is lag by one month. For example, this panel considers a performance of factor timing investing during the month after the recession months (so the months in which the return is calculated might, or might not continue to be a recession).

Panels A and B thus address different issues: Panel A takes the perspective of an investor who stands at the end of each month, looking back at the performance of factor timing in relation to the economic environment experienced during the same month. This perspective cannot be used to make the timing decisions in the portfolio because the economic environment was not known ahead of time. In contrast, panel B takes the perspective of an investor who stands at the beginning of each month looking at the performance of factor timing in the coming months in relation to the economic environment experience in the previous month.

Such a perspective analysis could be used to time a trading strategy, in principle, but we note several caveats. First, certain variables are not known in real time (e.g., the dating of recessions), and second, the classification of low versus high inflation is performed ex post. In any event, Panel B shows the performance of factor timing was similar across crises (e.g. high inflation periods, recessions, bear markets). Hence, whereas panel B shows the apparent potential ways in which we could improve the strategy through timing decisions, Panel A shows that the factor timing strategy, under full information assumptions, serves

Exhibit 10

Factor Momentum across Economic Regimes: Quintiles

Macro Indicator	Statistic	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Panel A: Factor Momentum Returns by Contemporaneous Macro Indicators						
S&P Volatility Level (Horizon: 36 Months)	Excess return	-1.5%	0.9%	-1.5%	1.1%	-4.7%
	(t-statistic)	0.94	0.51	0.33	0.25	0.19
	Volatility	1.4%	1.6%	3.1%	2.1%	3.2%
	Sharpe ratio	-1.08	0.58	-0.50	0.51	-1.48
S&P Volatility Change (Horizon: 36 Months)	Excess return	-3.3%	-0.7%	2.9%	-1.8%	0.1%
	(t-statistic)	0.86	0.49	0.35	0.25	0.20
	Volatility	1.7%	1.7%	1.9%	2.3%	3.8%
	Sharpe ratio	-1.94	-0.43	1.56	-0.78	0.02
T-Bill Yields	Excess return	-3.2%	-3.2%	1.0%	-1.4%	4.5%
	(t-statistic)	0.86	0.47	0.34	0.25	0.21
	Volatility	2.0%	1.3%	3.3%	1.8%	3.5%
	Sharpe ratio	-1.61	-2.43	0.30	-0.81	1.29
Panel B: Factor Momentum Returns by Contemporaneous Lagged Macro Indicators						
S&P Volatility Level (Horizon: 36 Months)	Excess return	-1.3%	0.0%	2.4%	-3.7%	-2.2%
	(t-statistic)	0.94	0.50	0.34	0.24	0.20
	Volatility	1.5%	1.8%	3.9%	2.1%	1.9%
	Sharpe ratio	-0.88	0.03	0.60	-1.76	-1.15
S&P Volatility Change (Horizon: 36 Months)	Excess return	-4.6%	1.8%	1.2%	-1.7%	-0.5%
	(t-statistic)	0.81	0.52	0.34	0.25	0.20
	Volatility	1.8%	1.6%	3.0%	1.9%	4.3%
	Sharpe ratio	-2.51	1.08	0.40	-0.89	-0.11
T-Bill Yields	Excess return	-6.0%	0.0%	-2.0%	-0.1%	5.4%
	(t-statistic)	0.75	0.50	0.32	0.25	0.21
	Volatility	2.2%	1.2%	3.3%	1.7%	3.5%
	Sharpe ratio	-2.76	-0.04	-0.61	-0.08	1.52

Notes: This exhibit shows the performance of the factor timing strategy before fees and after simulated transaction costs. For each economic regime, we report the strategy's annualized excess return, its t-statistic, volatility, Sharpe ratio. We consider the economic indicators: S&P volatility (estimated over the most recent 36 months), the 3-month changein the estimated volatility, and the T-bill yield. For each indicator, we sort the data into quintiles. Panel A reports the contemporaneous factor timing performance, and Panel B reports the factor timing performance in the following month.

as a robust way to express views regarding upcoming crises.

In **Exhibit 10**, we consider the different economic indicators, while separating the time periods into quintiles (because each of the indicators are numerical, rather than binary variables such as recession or boom). In particular, we consider the S&P volatility (estimated over the most recent 36 months), the three month change in the estimated volatility, and the T-bill yield. Panel A reports the contemporaneous Factor timing performance, while panel be reports the performance in the following month (or, said differently, The economic indicator is lagged one month, as in Exhibit 9, Panel B).

Starting with the first row of **Exhibit 10, Panel A**, we see that the factor timing strategy has performed best in quintiles two and four where, as we mentioned in our prior section, the volatility is high but, not

Exhibit 11

Regressions of Factor Timing Strategy against various economic indicators, 1999-2019

Configuration No.	Constant	USRecLag	USInfLag	Stagflation	F-statistic	Significant
1	-0.001%				0.12	no
T-stat	-0.35					
2	-0.002%	0.009%			0.33	no
T-stat	-0.57	0.73				
3	-0.012%	0.006%	0.020%		2.63	yes
T-stat	-2.22	0.48	2.69			
4		0.001%	0.009%		1.48	no
T-stat		0.08	1.62			
5				0.06%	16.40	yes
T-stat				4.05		
6	-0.005%	-0.071%	0.007%	0.128%	8.83	yes
T-stat	-1.02	-3.76	0.88	5.24		
7			0.001%	0.057%	8.23	yes
T-stat			0.24	3.67		

Notes: This exhibit shows the OLS regression loadings of the factor timing strategy (net of fees, gross of costs) regressed against various economic indicators. For each configuration, we report the strategy's loadings and t-statistics, respectively, for each economic indicator. The economic indicators are USRecLag a one month lagged binary "recession vs. boom" indicator as defined by NBER Business Cycle Dating Committee; USInfLag a one month lagged binary "inflation: low vs. high" based on U.S. CPI from 1999 to 2019, based on Shiller [2000] who uses the Warren and Pearson [1935] price index; and Stagflation a one month lagged product of USRecLag and USInfLag.

too high, and low but, not too low, Although this result could simply reflect randomness in the data because the t-statistics are not significant.

Further, the performance has been highest during periods of little change in volatility, though we cannot say this with regards to statistical significance. We can take this result as meaning that analytically because our indicator is looking at past performance and extrapolating it to the future, the certain statistical moments would need to stay constant for our indicator to perform well. Turning to panel B, we see a different pattern, which could be related to the lack of statistical significance of the economic indicators.

Cross Cycle Factor Timing Significance

In prior sections, we discovered that our factor timing strategy outperforms our factor benchmarks in a statistically significant way in months after a recession or high inflation period.

We would like to now test these conclusions using OLS regression analysis. Our dependent variable is the return of our factor timing strategy net of the performance of our factor benchmark. Our independent variables are our indicators for recession and inflation, discussed in prior sections, and our stagflation indicator which is equal to the product of our recession and our inflation indicators.

In **Exhibit 11**, we test the statistical significance of recessions and high inflation periods as well as periods in which both a

Exhibit 12

Performance of Updated Factor Timing strategy, 1999-2019

Time Period	Return Net of fee	Returns Net of 2/20 Fee, Net of Cost	Realized Volatility	Sharpe Ratio	Correlation with S&P	Correlation with Equal Weighted Factor Portfolio	Correlation with 10-year US Treasury Bond
1999-2000	1.9%	0.6%	3.2%	0.17	-0.01	1.00	-0.01
2001-2005	12.9%	7.5%	3.9%	1.92	-0.30	0.91	-0.24
2006-2010	11.1%	6.2%	3.2%	1.95	-0.19	0.56	-0.11
2011-2015	5.1%	2.0%	3.1%	0.64	0.36	1.00	0.14
2015-2019	5.5%	2.2%	4.5%	0.49	0.12	1.00	-0.04
Full Sample	9.1%	4.6%	4.5%	1.03	-0.10	0.78	-0.06

Note: This exhibit shows the strategy's annualized excess returns (i.e., returns in excess f the risk-free interest rate), before and after simulated transaction costs, and gross and net of hypothetical 2-and-20 fees.

recession and high inflation occur which we label stagflation. We present 7 different configurations and we will select the top model based on its F-statistic and significance using the F-test.

We can see from configuration number 1 that, overtime, our factor benchmark has outperformed our factor timing portfolio but, in a nonsignificant way. We can also see that recessions are not predictive of timing outperformance.

Looking at configuration numbers 3 and 4, we can see that inflation is a significant predictor of factor timing outperformance over factors if recognize factor timing's tendency to underperform our factor benchmark. The difference between configuration number 3 and number 4is that when we do not assume a constant rate of performance, we relegate the underperformance of our factor timing strategy relative to our factor benchmark as variance; which our predictive indicators cannot explain.

Looking at configurations 4, 5, and 6, we can see that stagflation is the most significant predictor of factor timing outperformance over the factor benchmark. We see that the signs of the factor loadings for the constant variable in configurations 1,2,3, and 6 are similar and confirm that, factor returns can only be timed during certain time in a cycle. We see from the recession loading in configuration 6 that recessions cannot predict an investors ability to time factors. Finally, turning our attention to stagflation we see that stagflation has the ability to predict factor timing opportunities. We conclude from this analysis, using the F-statistic, that our stagflation indicator is the only indicator that we need to worry about with for predicting timing opportunities.

Pivoting to Factor Timing during periods of stagflation

In our prior section, we concluded that stagflation is a predictor of our opportunity to time the market. Having concluded this about our indicator, we wish to integrate this feature into our factor timing strategy.

In **Exhibit 12**, we show the performance of a strategy that goes long our factor timing strategy while shorting our equally weighted factor benchmark following a month in which our indicator shows stagflation and going long our factor benchmark during all other periods.

Our improved model produces an average Sharpe ratio of 1.03 with an average correlation of -.1 to the S&P 500 and a correlation of -.06 to 10-year Treasury bonds, net of hedge fund fees and transaction costs. It should be noted that during the periods in which there was stagflation, our improved strategy produced a Sharpe ratio of around 2. These results are consistent with the Pruitt and Kelly (2018) where the authors conclude that autocorrelation does not exist in a full information world rather, autocorrelation exists as a proxy for unknown factors.

The standard trade-off in investments is typically stocks vs bonds; stocks benefit from a growing economy while bonds benefit from low inflation. A stagflation scenario is unfavorable to both stocks and bonds and as such, the representative investor lacks the intuition to invest in either stocks or bonds and runs to the safety of cash. In such a scenario, autocorrelation acts as the only form of intuition from which an investor can select investments in a long/short manner because the investor still has no intuition about the benchmark.

Exhibit 13

Sharpe Ratio difference between Updated Factor Timing Strategy and Factor Timing strategy, 1999-2019

Time Period	Difference in Sharpe Ratio
1999-2000	0.03
2001-2005	0.14
2006-2010	1.69
2011-2015	-0.04
2015-2019	0.62
Full Sample	0.58

We can conclude from the negative correlations of our strategy to both stocks and bonds in **Exhibit 12** that our theory is consistent with our data. Additionally, as depicted in **Exhibit 13**, the incorporation of our stagflation indicator to time our use of our factor timing strategy improves our Sharpe ratio by 0.58 indicating that this improvement in our model significantly enhances the performance and economic significance of our strategy.

Conclusion

Can you time factors? In equilibrium? No. During stagflation? Yes. We find that transactions costs stamp out factor timing unless there is stagflation. Pruitt and Kelly (2018)'s conclusions about factors explaining away momentum are echoed by our paper in cases other than stagflation. During stagflation periods, liquidity is highly sought after by market participants and, as such, market efficiency weakens to the point of weak market efficiency and allows a representative investor to leverage price signals in the pursuit of profits. We find that a portfolio which invests in an equally weighted benchmark of all factors during non-stagflationary periods and invests in a long-short portfolio which goes long the factors that have gone up in at least two of the three test periods (3 months, 6 months, 12 months) and short our equally weighted benchmark of all factors produces a Sharpe ratio 1.03 (4.6% return, 4.5% volatility) net of transaction costs, 2% management fee, and 20% performance fee and is also negatively correlated to both 10-year Treasury bonds and the S&P 500.

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