The Impact of Fiscal and Monetary Policy on the Cross-Sectional Value Factor

by

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Abstract

I find strong evidence that the cross-sectional value factor's returns are impacted by fiscal and monetary policy in the post-Bretton Woods era. Using a custom set of 768 value factors formed on the intersection of five portfolio construction design choices, which I take to represent the concept of the "value" premium in aggregate, I find that both structural and revaluation returns to the factor are lower than average during periods when fiscal and monetary policy are jointly loose. Oppositely, when each policy is tight, total and decomposed returns to value are all higher than average. My findings provide an explanation for at least part of the time-varying nature of value's returns. Factor timing strategies that tactically utilize the information contained in fiscal and monetary policy weakly improve on strategic allocations to value over the long-run.

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I firstly and primarily thank Mark Kritzman for his very generous time and support throughout my project. Many of the ideas and analyses I ultimately pursued within are due to his guidance and own research. Indeed, I cite several of his numerous excellent papers in my own work, and my factor timing strategies are all primarily based on his latest relevance-based prediction methodology, a unique and highly flexible approach that I intend to utilize in extensions of this paper in the future. I was very fortunate to take part in his proseminar course in capital markets/investment management during the fall semester, and am very grateful that he accepted me as a student for this thesis. It was truly a pleasure to learn from him throughout the year.

I am also forever grateful to my wife, Colleen Roney, for her love and support. We moved from Charlottesville, Virginia so that I could study for my Master of Finance degree here at MIT Sloan, no doubt a difficult move given it was where we met at the University of Virginia, got engaged and married, and began building a life together. She has sacrificed so much so that I could pursue my passion of finance here at MIT, and I am certainly a better person in all senses of the word because of her. I appreciate and love her.

We have not been alone here in Boston though. Throughout our year here, my parents, Richard and Rachel Suvak, as well as my brother, Cristian Wood-Suvak, and his wife, Michaela, have all been fantastically supportive in more ways than I can list here. One major reason why I ended up choosing MIT Sloan's Master of Finance program over others I was accepted into was to be close to them. After being away for the prior seven years, it has been a very welcome change to be nearby to family. Together with Colleen, I view my graduation from MIT as a celebration of not only my work but the support of my family, and I write this paper as a testament to our achievements and enduring relationship.

The question I have attempted to answer is not the result of a recent interest. In my undergrad at the McIntire School of Commerce at the University of Virginia, I explored a similar but broader question about the impact of fiscal and monetary policy on common equity market risk factors generally, under the guidance of Professor David Chapman. His supervision laid the groundwork for what has ultimately manifested in this paper, and his support in the application process to MIT Sloan was absolutely invaluable.

My specific focus on value was sparked by my time on the Asset Allocation team at Investure, LLC in Charlottesville, a topic that we thought very deeply about and identified as a tactical opportunity as early as late 2019. I sincerely thank Hance West, Scott Mootz, Vitali Bezouchko, Derek Anderson, Frederick Nolde, and the rest of the team at Investure for many robust discussions and for nurturing an intellectually curious environment in which I could begin to shape not only my career, but also more importantly my investing philosophy. Of course, I would likely not be in the MFin program without the specific support of Hance and Scott, for which I am very grateful.

Contents

List of Figures

List of Tables

1 Introduction

The HML cross-sectional equity market value factor of Fama and French (1993) has from 1926 to 2022 experienced rolling 3-year annualized returns ranging from -18.2% to 26.3%, with an average of 3.7%[1]. What explains the time-variation in the returns to this asset pricing factor? I propose that at least part of this variation can be explained by both the levels of and changes in fiscal and monetary policy. More specifically, I hypothesize that the revaluation return to the value factor, in a decomposition of its returns into structural and revaluation components following Arnott, Harvey, Kalesnik, and Linnainmaa (2021), is the primary mechanism through which the impact of the joint policy regimes operates in the medium-term.

My investigation is based upon, among others, the duration-based asset pricing theories of both Lettau and Wachter (2007) and Gormsen and Lazarus (2019), who argue that value stocks have lower cash flow duration exposure than growth stocks. The implication is that the value factor is exposed to monetary policy through the discount rate channel. Indeed, Campbell and Vuolteenaho (2004) show that growth stocks have higher betas with respect to related discount rate news than value stocks in the post-1963 period. I therefore test this hypothesis in the post-Bretton Woods period from the end of 1972 onwards, the beginning of the modern international monetary system, by using a custom set of 768 unique U.S. value factors formed on the intersection of five portfolio construction design choices: 1) ratio variables ("signal"); 2) market capitalization universe ("size"); 3) signal breakpoints ("value"); 4) sub-portfolio weighting ("weight"); and 5) sub-portfolio sector schemes ("sector"). Taken together, I define the universe of these value factors to represent the concept of the "value" premium in aggregate, known to exist since the seminal paper of Fama and French (1992). Supporting this, Kessler, Scherer, and Harries (2020) show with a much broader set of 3,168 value factor designs that the premium is multi-faceted along similar dimensions to the design choices that I employ.

My approach is to evaluate this set of factors in totality and specifically primarily using panel regression methodologies. With respect to the first assessment, the creation of this set of factors, rather than a focus on any individual one that could be subject to overfitting bias, as found in part for the value factor by Ilmanen, Israel, Lee, Moskowitz, and Thapar (2021), allows me to examine whether the impact of fiscal and monetary policy is actually robust enough to survive differences in portfolio construction. For example, an investor may desire to take value factor exposure in line with the original Fama and French (1993) specification, but may choose to hold only the top and bottom 10% of firms for the long and short sub-portfolios, respectively, as opposed to using the arbitrary 30% cutoffs along the book-to-market equity ("B/M") spectrum from the original paper, so as to minimize the amount of trading required. If the HML factor is found to be influenced by

[1] U.S. Research Returns Data (Downloadable Files). `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

fiscal and monetary policy variables, but this new "deep" HML is not, that result would call into question whether the two policies actually impact value versus growth cross-sectional returns at all, and at very least would weaken any results for the former. More generally, if only around 5% of factors experience some kind of influence from fiscal and monetary policy, and these results are not consistent, I would not be able to reject the null hypothesis that there is no impact in aggregate when accounting for the issue of multiple testing.

With respect to the second more specific assessment, I also use my set of factors to evaluate whether there are certain "styles" of value that are more impacted by fiscal and monetary policy than others. For example, perhaps small cap stocks (in the context of the value factor), which over the full long-run sample have CAPM betas that are higher than large cap stocks after controlling for valuation, respond more in aggregate to policy regimes than stocks in other capitalization segments, since these stocks are more exposed to events in the macroeconomy. It may also be the case that certain signal definitions, for example the earnings ratios, respond more to the policies than value factors based on balance sheet or cash flow ratios that potentially reflect differences in the types of businesses grouped in each sub-portfolio. The results aggregated at these levels, assuming they are homogeneous within each category based on the other portfolio construction decisions that define my custom factor set, reveal something more specific about the time-variation in value factor returns that would not be accessible by examining one factor, no matter how simple or complex in its construction. This type of analysis across a broad swath of factors therefore allows for both a more holistic and nuanced perspective on how fiscal and monetary policy impact the returns and characteristics of "value", broadly defined.

In the sense that I am interested in evaluating how two exogenous policies impact the value factor, I employ multiple approaches. Firstly, I assess returns on a daily cadence around one of the more impactful policy-related events, namely Federal Open Market Committee ("FOMC") meetings. Bernanke and Kuttner (2005), among others, show that unexpected 25 basis point ("bp") cuts in the Federal Funds rate target are associated with approximately a 1% increase in broad stock indexes. I extend their methodology and additionally employ an event study of the form following Fama, Fisher, Jensen, and Roll (1969) and MacKinlay (1997). This "daily" approach is most indicative of the short-run response of the cross-section of returns to news about monetary policy, controlling for broader policy and macroeconomic conditions. Secondly, and of primary emphasis in this paper, is a longer-run "monthly" evaluation of value factor performance and characteristics in and across policy regimes. I define each policy to be expansionary/loose and contractionary/tight using parsimonious and transparent methodologies previously identified in the literature, including by Bohn (1998) for fiscal policy and Taylor (1993) for monetary policy, and run a battery of tests to evaluate the decomposed value factor's performance by regime and in the full sample.

Importantly, I not only provide an explanatory account of the impact of fiscal and monetary policy on the cross-sectional value factor, but also assess whether the information contained in these policies is useful in constructing a factor timing strategy. Several papers, such as Asness, Friedman, Krail, and Liew (2000), Asness (2016a), Arnott, Beck, and Kalesnik (2016a), Arnott, Beck, and Kalesnik (2016b), Asness, Chandra, Ilmanen, and Israel (2017), Bender, Sun, Thomas, and Zdorovtsov (2018), Czasonis, Kritzman, and Turkington (2020a), and Ilmanen, Israel, Lee, Moskowitz, and Thapar (2021) evaluate various factor timing strategies, including as they specifically relate to the value factor. I use several approaches to construct a timing strategy, primarily constructed with a unique and flexible out-of-sample methodology suggested by Czasonis, Kritzman, and Turkington (2023).

The rest of this paper is organized as follows. Section 2 reviews the literature around the value factor, as well as on fiscal and monetary policy. Specifically, I highlight the time-varying nature of the value premium in the post-Global Financial Crisis ("GFC") era, as well as fiscal and monetary policy regime identification and their impacts on financial markets. Section 3 discusses the data I use, the regime classification methods I employ, and the empirical analyses I perform, while Section 4 presents the results of those analyses. In this section, I distinguish between two types of results: 1) the "daily" event study analyses; and 2) the "monthly" regime-based approach. Section 5 then formulates and tests various factor timing strategies based on the results from Section 4 and the regressions advocated by Czasonis, Kritzman, and Turkington (2023). Finally, Section 6 concludes.

2 Literature Review

2.1 The Value Premium

From the early discoveries of Rosenberg, Reid, and Lanstein (1985) and Fama and French (1992), many papers have together clearly identified a premium for value stocks relative to growth stocks in the cross-section. However, considerable debate still revolves around the source of this premium, as discussed early after its discovery by Daniel and Titman (1997), for example. As summarized by Asness, Frazzini, Israel, and Moskowitz (2015), one camp proposes a behavioral theory, such as in DeBondt and Thaler (1985) and Daniel, Hirshleifer, and Subrahmanyam (1997), while the other posits a rational, risk-based theory, such as in Fama and French (1996). This debate makes the question of what drives the time-variation in the value factor's returns difficult to answer.

Nevertheless, in the past few years, much ink has been spilled discussing the value factor's woes in the post-GFC period. From June 2009, when the National Bureau of Economic Research ("NBER") defines the Great Recession to have ended[2], to December 2022, the HML factor of Fama and French (1993) generated an annualized return of -0.5%, compared with the 12.6% annualized excess return of the CRSP value-weighted index. Practitioners, including Inker (2022) and Arnott and Ko (2023),

[2] US Business Cycle Expansions and Contractions. `https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions`

among others[3], have emphasized the importance of the role of changing relative valuation levels between the value and growth sub-portfolios to explain the performance of value during this time period.

Academics, for their part, have also devoted considerable pages to explaining what has driven the returns to value in the past decade. Some papers, including Fama and French (2021), Blitz and Hanauer (2021), and Goncalves and Leonard (2022) suggest that the main culprit is the use of the classic B/M characteristic to form value factors. They argue that this metric is either no longer a useful one in a period in which intangible capital is increasingly large relative to tangible investments, following Peters and Taylor (2017), or that the premium has mostly disappeared altogether since its discovery, perhaps in line with the degradation of returns post-publication finding by McLean and Pontiff (2016). Other papers suggest that the factor has historically experienced a wide relative valuation primarily as a result of worsening fundamentals, as in Asness, Liew, Pedersen, and Thapar (2021), or a negative premium due to differences in intangible and tangible investment rates, as suggested by Kazemi (2022). Still others, such as Israel, Laursen, and Richardson (2021) and Bellone and de Carvalho (2022), argue that it has been irrational expectations of future performance that have manifested in relative valuation changes between the value and growth sub-portfolios, and that fundamentals have been of less importance to investors in the past few years as a sign of this possible exuberance. Ang (2023) characterizes the returns to value, among other cross-sectional asset pricing factors, as occurring in trends and cycles, offering a useful comparison to prior drawdowns.

My aim in this paper is to provide an additional possible explanation for the time-variation in the value factor's returns, particularly in light of its poor performance during the post-GFC period, using joint regimes of fiscal and monetary policy.

2.2 Fiscal Policy

One potential problem that occurs in analyzing the effect of fiscal policy on asset markets generally, and therefore also the value factor specifically, is the type of economy assumed. For example, Chatziantoniou, Duffy and Filis (2013) assert that the economic impacts of fiscal policy on equity markets depends on whether a Keynesian, classical, or Ricardian view of the economy is adopted. They contend that the effects of policy may be positive, negative or inconsequential depending on these three views, respectively. Additionally, Cochrane (2023) emphasizes the Ricardian question in particular, which is exacerbated by the interaction of fiscal and monetary policy as discussed by Baz, Davis, Beck-Friis, Tsai, and Zhang (2021). However, my paper focuses on the empirical effects of fiscal policy on the value factor, and thus mostly ignores these complications. Indeed, I take an approach similar to Czasonis, Kritzman, and Turkington (2020b), who offer a purely empirical account of fiscal and monetary policy.

[3] For additional context, please also see AQR (2022).

A further issue, however, is that of endogeneity. Various papers, including Jaeger and Schuknecht (2007), Tagklakis (2011a), Tagkalakis (2011b), and Agnello and Sousa (2013), show that there is a bidirectional effect between fiscal policy and asset prices. These papers primarily emphasize broad stock market indexes and housing prices in their evaluations. My focus on the value factor, however, mostly mitigates this concern as legislators are presumably not focused on the systematic cross-section when making discretionary fiscal policy decisions.

Perhaps one of the first papers addressing the empirical link between fiscal policy and stock returns is Darrat (1990), who uses the change in real high-employment budget deficits (adjusted for automatic stabilizers) relative to real GNP as a measure to assess fiscal policy's impact on markets. Many papers, including Ardagna (2009), Afonso and Sousa (2011), Afonso and Sousa (2012), and Liu (2023), use this and related approaches to document that positive shocks to fiscal policy generally lead to declines in stock prices, while periods of fiscal tightening are generally supportive of equity markets.

Compared with broader financial markets, there has been considerably less work on the impact of fiscal policy on the cross-section of stock returns, and in particular on the value factor. Two papers that examine the cross-section are Belo, Gala, and Li (2013) and Brogaard and Detzel (2015), whose work I draw on for methodological motivation. For example, the latter uses the economic policy uncertainty ("EPU") index of Baker, Bloom, and Davis (2016) to conclude that fiscal policy, a major component of the EPU index, is an economically important risk factor; I explicitly make use of the EPU index in various ways in my own analyses.

With respect to fiscal policy regime identification, many papers have have measured and classified the stance of fiscal policy using forms of Markov-switching models, including vector autoregressive ("VAR") and dynamic stochastic general equilibrium ("DSGE") classes of models. For example, Bianchi (2012) uses a Markov-switching DSGE model to classify fiscal and monetary policy as active or passive. An issue with these types of models, however, is once again the endogeneity effect, as identified by Change, Kwak, and Qui (2021), among others; fiscal and monetary policy react to one another and prevailing economic conditions in a complex system of bidirectional causation. I therefore adopt a more parsimonious and transparent approach motivated by Bohn (1998), operationalized by Mauro, Romeu, Binder, and Zaman (2015), and tested by Banerjee, Boctor, Mehrotra, and Zampolli (2022), among others. I discuss fiscal policy regime identification in more detail in the Data and Methodology section.

2.3 Monetary Policy

Papers such as Jansen, Li, Wang, and Yang (2008) and Laopodis (2009) argue that the impact of monetary policy on markets is larger than that of fiscal policy, even though the latter's stance is a contributory factor. Furthermore, given the importance of central bank independence and time-consistency in the U.S., as advanced by Kydland and Prescott (1977), an investigation into monetary policy's impact on markets, and specifically the cross-sectional value factor, is less complicated by theoretical concerns than fiscal policy. Nonetheless, some issues remain, including the time-varying importance of monetary policy to markets. Indeed, both Chen (2007) and Kurov (2010) document that monetary policy has larger effects on stock returns during bear markets. As such, I again emphasize an empirical approach over a long time horizon, and in various sections make use of the Mahalanobis similarity methodology of Kinlaw, Kritzman, Metcalfe, and Turkington (2023) to mitigate this problem.

Immediately prior to and during the Volcker years, many papers chose to focus on the role of inflation in a rules-based system to maintain price stability, which indirectly links monetary policy with equity markets. Fama and Schwert (1977) show that stock returns are negatively related to expected inflation, and also to the unexpected component of that inflation. This result is confirmed by Schwert (1981), who focuses explicitly on the unexpected component of inflation in the consumer price index ("CPI").

As inflation stabilized following the Volcker era, it became clear that the Federal Reserve was committed to stabilizing the inflation rate. Many papers then chose to examine the link between monetary policy and equity markets in a more direct fashion. While the literature approaches this task in many different ways, a common theme in papers such as Thorbecke (1997), Kuttner (2001), Bomfim (2003), Rigobon and Sack (2004), Bernanke and Kuttner (2005), and Chava and Hsu (2020) is to examine unexpected innovations in monetary policy on FOMC announcement dates and other important "Fed speak" events to assess the exogenous impact of (surprise) policy decisions on markets. Most of these papers, particularly following Kuttner (2001), make use of Fed Funds futures contracts to measure the expected and unexpected components of target rate changes, a methodology I similarly employ in my paper. Various asset pricing implications fall out of this strand of literature, including in Detzel (2017) and Ozdagli and Velikov (2020). The latter, for example, create a monetary policy exposure ("MPE") index and sort stocks into portfolios of exposure, finding that stocks with positive responses to expansionary monetary policy earn lower average returns than those stocks with less positive/negative responses.

In the cross-section, the literature takes different approaches to measuring monetary policy's effect. Ehrmann and Fratzscher (2004) show that stocks react heterogeneously to monetary policy based on Tobin's q theory of investment, such that stocks with a high Tobin's q are more exposed to changes in policy. Ippolito and Ozdagli (2018) argue that financially constrained firms have greater sensitivity to monetary policy not just in their stock price, but also in various fundamental characteristics such as cash holdings, inventory, and fixed capital investment. Other papers, including Jensen and Mercer (2002) and Neuhierl and Weber (2017), document a potentially new cross-sectional asset pricing factor that improves on the Fama and French (1993) three factor model.

With respect to monetary policy regime identification, one approach to policy classification that may be useful in possible extensions of this paper to a global set of markets is the work of Romelli (2022), who creates an index of central bank independence using a novel dataset of 154 countries over a long sample from 1972. In this paper, I use a simpler approach primarily based on the work of Taylor (1993), discussed in more detail in the Data and Methodology section.

3 Data and Methodology

3.1 Data

3.1.1 Factor Data

I study a custom set of 768 U.S. value factors motivated by, but intentionally more narrow in scope than, Kessler, Scherer, and Harries (2020). Return data for the underlying stocks is from CRSP and accounting data is from Compustat. All variables are measured in U.S. dollars using spot exchange rates from Bloomberg (for Canadian firms) averaged over relevant periods depending upon the horizon of each metric; for example, annual (quarterly) sales data is converted using trailing 12 (3)-month average spot rates, while balance sheet information is translated using financial statement date spot rates.

I focus on the non-micro common stock universe for those stocks traded on the NYSE, Nasdaq, and AMEX exchanges with market capitalizations above the NYSE 20th percentile. With respect to the CRSP data, I include delisting returns and set them to -30% if they are missing and the delisting is for a performance-based reason, following Shumway (1997). For both the CRSP and Compustat data, I generally make use of the variable definitions laid out in meticulous detail by Jensen, Kelly, and Pedersen (2021), with support from WRDS Research[4], including specifically the 2022 update to the Python replication of the Fama and French (1993) factors using the updated CRSP CIZ data format[5]. One of the primary additions I make to their suite is the modified book equity value of Peters and Taylor (2017), which includes estimates of firm knowledge and organization capital that together comprise intangible capital; I apply their simpler measure assuming $G_{i0} = 0$, which they report gives an even stronger investment-q relationship than their main measure. For the Compustat data, I assume that accounting variables are publicly available four months after the end of the accounting period. I create each characteristic separately using the annual and quarterly data, and later combine these two sources by always making use of the most recent available data. For the quarterly income and cash flow statement data, I always take the sum of the item over the past four quarters to avoid seasonality issues and to ensure comparability with the annual data.

[4] WRDS Research. `https://wrds-www.wharton.upenn.edu/pages/wrds-research/`

[5] Fama-French Factors (Python - CIZ Format). `https://wrds-www.wharton.upenn.edu/pages/wrds-research/applications/python-replications/fama-french-factors-python-ciz-format/`

Table 1: Signal Definitions

Signal	Signal Abbreviation	Signal Group	Example Supporting Paper
Book-to-Market Equity	be_me	Balance Sheet	Rosenberg, Reid, and Lanstein (1985)
Modified Book-to-Market Equity	mbe_me	Balance Sheet	Peters and Taylor (2017)
Assets-to-Market Equity	at_me	Balance Sheet	Fama and French (1992)
Sales-to-Market Enterprise Value	sale_mev	Enterprise Value	Asness, Friedman, Krail, and Liew (2000)
Operating Profit-to-Market Enterprise Value	op_mev	Enterprise Value	Ball, Gerakos, Linnainmaa, and Nikolaev (2015)
EBITDA-to-Market Enterprise Value	ebitda_mev	Enterprise Value	Loughran and Wellman (2011)
EBIT-to-Market Enterprise Value	ebit_mev	Enterprise Value	
Operating Profit to Equity-to-Market Equity	ope_me	Earnings	Fama and French (2015)
EBT-to-Market Equity	pi_me	Earnings	
Net Income Incl. Extraordinary Items-to-Market Equity	nix_me	Earnings	Kessler, Scherer, and Harries (2020)
Net Income Excl. Extraordinary Items-to-Market Equity	ni_me	Earnings	Basu (1983)
Operating Cash Flow-to-Market Equity	ocf_me	Cash Flow	Desai, Rajgopal, and Venkatachalam (2004)
Free Cash Flow-to-Market Equity	fcf_me	Cash Flow	Lakonishok, Shleifer, and Vishny (1994)
Dividend Yield	div_me	Yield	Litzenberger and Ramaswamy (1979)
Payout Yield	eqpo_me	Yield	Boudoukh, Michaely, Richardson, and Roberts (2007)
Net Payout Yield	eqnpo_me	Yield	Boudoukh, Michaely, Richardson, and Roberts (2007)

This table summarizes the signals and signal groups that I use to form my custom set of 768 value factors. Underneath each individual signal are 48 specific portfolio construction design choices, formed on the intersection of size, value, weight, and sector. I use the signal abbreviation column throughout various parts of this paper.

I construct monthly-rebalanced, long/short, zero-net investment factors over the December 1972 to December 2022 period, and do so using the most recent price data following the work of Asness and Frazzini (2013). The 768 value factors, fewer in quantity than Kessler, Scherer, and Harries (2020) primarily because of my emphasis on the classic zero-net restriction between the long and short sub-portfolios, are formed on the intersection of 16 signals, four market capitalization segments, three value breakpoints, two sub-portfolio weighting allocations, and two sub-portfolio sector schemes. A summary of the signals that I use is given in Table 1.

Each of those signals are applied to the 48 other unique construction design choices across the size, value, weight, and sector categories. With respect to size, following Jensen, Kelly, and Pedersen (2021) I define small cap stocks ("small") to be those with market equity values falling between the 20th and 50th percentiles of the NYSE, large cap stocks ("large") to fall between the 50th and 80th percentiles, and mega cap stocks ("mega") to be above the 80th percentile. I also separately categorize an all cap universe ("all"), where all stocks above the non-micro 20th percentile of NYSE market capitalization are included. Then, each month and within each size category, I sort stocks into NYSE-based characteristic deciles for "deep" value factors, three portfolios at the 30th and 70th percentile breakpoints for "moderate" value factors, and two portfolios at the 50th percentile breakpoint for "shallow" value factors. Each value factor then goes long the highest characteristic sub-portfolio and short the lowest characteristic sub-portfolio, since all signals are defined on a yield basis. I distinguish between market value-weighted ("VW") and equal-weighted ("EW") allocations as two possible approaches to sub-portfolio weighting. Finally, the sector-neutral ("SN") sub-portfolio scheme is the same as the sector-agnostic ("SA") approach described previously, except that at the sorting stage, each stock's sector median characteristic value is subtracted from each stock's raw characteristic value and sorted after the neutrality adjustment, following Kessler, Scherer, and Harries (2020).

Though I track dozens of returns-based and fundamental characteristics at the sub-portfolio and value factor levels, I define the Peters and Taylor (2017) modified book-to-market equity value as my valuation measure of choice. The relative valuation spread between the long value and short growth sub-portfolios is defined as the ratio of the long sub-portfolio weighted-average B/M value to the short sub-portfolio weighted-average B/M value, such that:

$$Value\ Spread_t = \frac{(Value\ Portfolio\ mbe\_me)_t}{(Growth\ Portfolio\ mbe\_me)_t} \tag{1}$$

From here, I decompose each value factor's returns into structural and revaluation components following Arnott, Harvey, Kalesnik, and Linnainmaa (2021), with support from Cohen, Polk, and Vuolteenaho (2003), Fama and French (2007a), and Gerakos and Linnainmaa (2018). The revaluation return stems from changes in the relative valuation of the value and growth sub-portfolios. The structural component captures returns from fundamental differences in profitability and efficiency between the value and growth sub-portfolios, as well as the rebalancing/migration effect documented by Fama and French (2007b). Specifically, I define the following:

$$Revaluation\ Return_t = \frac{Value\ Spread_{t-1}}{Value\ Spread_t} - 1 \tag{2}$$

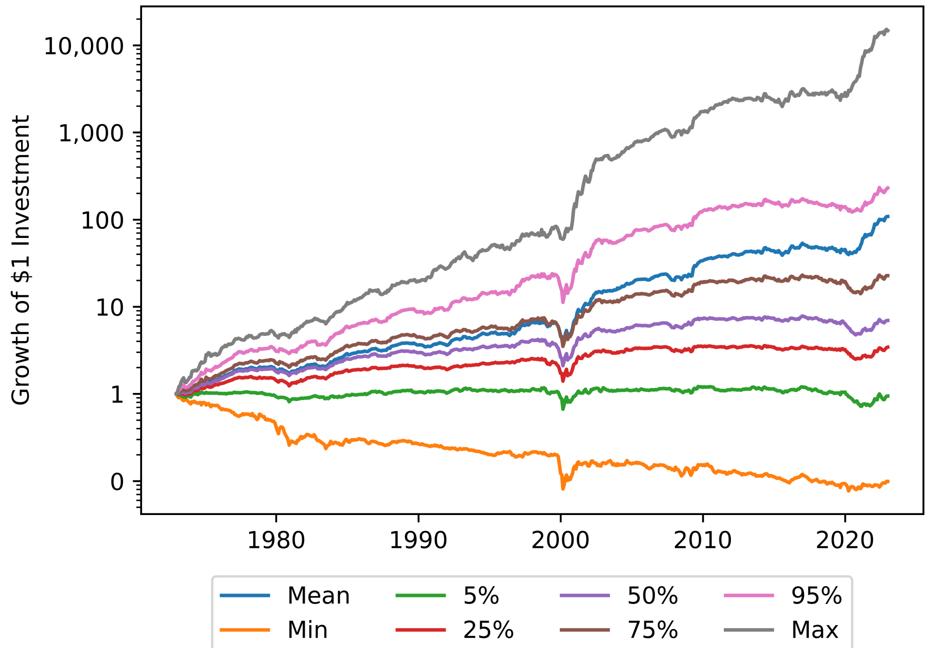
$$Structural\ Return_t = \frac{(1 + Total\ Return_t)}{(1 + Revaluation\ Return_t)} - 1 \tag{3}$$

Note that because each factor's $Value\ Spread$ is in the form of a yield, it must be inverted to the form of a M/B multiple in equation 2. Further, because the value factor is a low turnover strategy compared with other cross-sectional factors like momentum, the "wedge", as Ilmanen, Nielsen, and Chandra (2015) term it, between changes in valuations and realized returns between rebalancing dates is small[6].

My value factor returns and their decompositions very closely match those of Fama and French (1993), Asness and Frazzini (2013), Kesler, Scherer, and Harries (2020), Jensen, Kelly, and Pedersen (2021), and Arnott, Harvey, Kalesnik, and Linnainmaa (2021) across various robustness checks. Figure 1 depicts the percentiles of wealth evolution across the 768 value factors that I form, and table 2 documents various summary statistics aggregated by value factor signals.

[6]Please see Arnott, Beck, Kalesnik, and West (2016), Asness (2016b), and Asness (2021) for additional details.

Figure 1: Cumulative Wealth Evolution of Value Factors by Percentile



This figure summarizes the cumulative wealth evolution of all 768 value factors by taking new percentiles every month. December 1972 to December 2022.

Table 2: Value Factor Summary Statistics

		Annualized Return			Sharpe Ratio			Max Drawdown-to-Vol.			Pairwise Correlation		
Signal	Signal Group	5%	Median	95%	5%	Median	95%	5%	Median	95%	5%	Median	95%
be_me	Balance Sheet	2.0%	5.2%	14.4%	0.17	0.42	1.07	5.31	4.08	2.33	0.55	0.75	0.94
mbe_me	Balance Sheet	2.6%	6.4%	19.4%	0.21	0.56	1.15	4.53	3.53	2.10	0.56	0.76	0.94
at_me	Balance Sheet	0.4%	3.1%	9.7%	0.04	0.25	0.79	5.81	4.28	3.17	0.52	0.74	0.95
sale_mev	Enterprise Value	2.9%	5.6%	11.9%	0.31	0.50	0.89	5.59	4.62	3.03	0.49	0.72	0.93
op_mev	Enterprise Value	3.6%	7.0%	15.1%	0.36	0.58	0.99	5.11	3.95	3.09	0.56	0.76	0.94
ebitda_mev	Enterprise Value	2.7%	5.6%	12.0%	0.15	0.43	0.81	5.34	4.27	3.48	0.57	0.78	0.95
ebit_mev	Enterprise Value	2.2%	4.3%	10.2%	0.14	0.37	0.66	5.78	4.47	3.46	0.57	0.78	0.95
ope_me	Earnings	2.6%	4.9%	11.5%	0.16	0.38	0.76	5.42	4.34	3.26	0.55	0.77	0.95
pi_me	Earnings	0.1%	3.7%	8.7%	0.00	0.33	0.71	5.44	4.48	3.57	0.55	0.75	0.94
nix_me	Earnings	-0.7%	3.3%	8.3%	-0.04	0.30	0.69	5.42	4.50	3.55	0.56	0.76	0.94
ni_me	Earnings	-0.5%	3.6%	8.4%	-0.03	0.31	0.69	5.45	4.44	3.69	0.56	0.76	0.94
ocf_me	Cash Flow	2.4%	4.9%	10.2%	0.24	0.40	0.74	5.27	4.12	3.21	0.49	0.72	0.93
fcf_me	Cash Flow	1.1%	3.3%	7.5%	0.11	0.30	0.65	5.83	4.63	3.42	0.38	0.62	0.92
div_me	Yield	-2.5%	0.8%	4.8%	-0.16	0.06	0.46	6.39	4.98	3.61	0.47	0.72	0.94
eqpo_me	Yield	-0.0%	1.8%	6.8%	-0.00	0.19	0.63	5.67	4.46	3.32	0.38	0.69	0.93
eqnpo_me	Yield	-2.6%	0.8%	2.6%	-0.19	0.12	0.38	8.13	5.54	4.07	0.02	0.47	0.85
All Factors		-0.2%	4.0%	11.5%	-0.01	0.36	0.82	5.83	4.41	3.05	0.14	0.60	0.85

This table provides summary statistics for all 768 value factors aggregated by signal at various percentile levels within each signal category, as documented in table 1. "Vol." stands for Annualized Volatility. The All Factors row represents all 768 factors over the full sample aggregated holistically. Pairwise correlation averages exclude those perfect correlations of a factor with itself. December 1972 to December 2022.

3.1.2 Policy and Macroeconomic Data

I primarily make use of the Federal Reserve Economic Data ("FRED") database[7] for both daily and monthly policy and macroeconomic data items. Additional sources include the Congressional Budget Office[8] ("CBO"), the Federal Reserve[9,10,11], the work of Baker, Bloom, and Davis (2016)[12], the CFA Institute[13], Robert Shiller[14], and Bloomberg. Unless otherwise noted, all data I collect that are used in the monthly analyses are appropriately lagged to ensure point-in-time consistency with no look-ahead biases, thereby also representing news about each variable as discussed by Ilmanen, Israel, Lee, Moskowitz, and Thapar (2021). The advantage of this approach is that any significant results are implementable in timing strategy backtests, in the sense that all information would be available to investors throughout the history of my monthly analyses. The daily data is used as a purely explanatory account and is structured as news by its nature, and therefore is not lagged.

I discuss the specific policy and macroeconomic variables I employ and how they represent fiscal and monetary policy in the Methods subsection.

3.2 Methods

3.2.1 Daily Event Study

I examine the period from December 1988, when Fed Funds futures began trading at the Chicago Board of Trade, to December 2022. This window has the additional advantage that Fed Funds target rates were explicitly defined, as documented by Rudebusch (1995). Through December 2022, but excluding the zero lower bound ("ZLB") periods, there were 203 FOMC meetings held when markets were open, of which 123 involved no change in the Fed Funds rate, 48 led to an increase, and 32 resulted in a decrease.

I distinguish between an analysis of value factor returns on these FOMC meeting days following the procedures of Bernkanke and Kuttner (2005) and an event study analysis from 15 days prior to 15 days after each of these meetings, an admittedly arbitrary three week window but one which generally leads to non-overlapping observations between meetings while still examining a sufficiently long window for evidence of pre- or post-announcement return drift, following Lucca and Moench (2015). For the first approach, I run random effects panel regressions of the following form, where

[7] Economic Research: Federal Reserve Bank of St. Louis. `https://fred.stlouisfed.org/`

[8] Congressional Budget Office. `https://www.cbo.gov/data/budget-economic-data`

[9] Board of Governors of the Federal Reserve System: Policy Tools. `https://www.federalreserve.gov/monetarypolicy/openmarket.htm`

[10] Board of Governors of the Federal Reserve System: Federal Open Market Committee. `https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm`

[11] Federal Reserve Bank of Atlanta: Wu-Xia Shadow Federal Funds Rate. `https://www.atlantafed.org/cqer/research/wu-xia-shadow-federal-funds-rate`

[12] Economic Policy Uncertainty Index. `https://www.policyuncertainty.com/`

[13] CFA Institute: Stocks, Bonds, Bills, and Inflation (SBBI) Data. `https://www.cfainstitute.org/en/research/foundation/sbbi`

[14] Online Data Robert Shiller. `http://www.econ.yale.edu/~shiller/data.htm`

ΔFF refers to the Fed Funds rate target change, c_i represents the random effect, and e and u denote the expected and unexpected components of that change, respectively, derived from the Fed Funds futures market:

$$r_{i,t} = \alpha + \beta_{FF,i}\Delta FF_t + c_i + \varepsilon_{i,t} \tag{4}$$

$$r_{i,t} = \alpha + \beta_{e,i}\Delta FF_t^e + \beta_{u,i}\Delta FF_t^u + c_i + \varepsilon_{i,t} \tag{5}$$

Note that the ith value factor returns, $r_{i,t}$, are total returns, but because they are over such a short daily horizon between rebalancing periods, the total return here is almost entirely attributable to revaluation returns, a direct test of my primary hypothesis. In order to examine the impact on specific types of factors, I run panel regressions 4 and 5 using both the full set of 768 value factors, as well as separately using factors collected by signal group, signal, size, value, weight, and sector. For each regression, I also include various controls and interactions advocated by Bernanke and Kuttner (2005) and motivated by other papers such as Kurov and Stan (2018), such as: 1) a post-1994 binary variable to account for the period from which the FOMC began announcing changes in interest rates under Chairman Alan Greenspan; 2) binary variables for rate increases and decreases; 3) the daily percentage change in the EPU index of Baker, Bloom, and Davis (2016); and 4) a binary variable for when the EPU index is above the median relative to history on an expanding basis.

Although I specifically examine whether a random or entity fixed effects model is more appropriate to utilize for equations 4 and 5 by employing the Durbin-Wu-Hausman test, I nonetheless also assume that the variation across value factors is both random and uncorrelated with the independent policy variables. This assumption, based on the idea that policymakers are not particularly concerned with the specific cross-sections of stocks that I examine, leads more naturally to a random effects model. I employ such a model throughout my analyses unless otherwise noted, while continuing to test whether a fixed or random effects more is more statistically appropriate.

For the event study approach, I use the constant mean return model of MacKinlay (1997) as a measure of expected returns, since the value factor is independent of the returns to other well-known risk premiums in both the time series and cross-section. I average returns across all 48 factors underlying each of the 16 signals I employ, and then test for statistically significant differences in that average performance prior to and following FOMC meeting announcements, controlling for the policy action (i.e., no change, increase, or decrease) taken.

3.2.2 Policy Regime Classification

As discussed in the literature review, my approach to fiscal and monetary policy variables and regime classification is empirical and parsimonious in nature. I rely primarily on the work of Bohn (1998) and Mauro, Romeu, Binder, and Zaman (2015) for fiscal policy, Taylor (1993) for monetary policy, and Banerjee, Boctor, Mehrotra, and Zampolli (2022) for the joint regimes.

Fiscal Policy Bohn (1998), and later Bohn (2008), assesses whether the response of the federal government's primary surplus (revenue minus non-interest expenditure) as a percentage of GDP to changes in the public debt-to-GDP ratio is positive or negative over time. A positive response indicates an intertemporally satisfied budget constraint, while a statistically significantly negative figure suggests fiscal "profligacy", a term explicitly used by Mauro, Romeu, Binder, and Zaman (2015) when they operationalize Bohn (1998) to 55 countries and several test modifications.

For my own fiscal policy regime classification, I first examine the primary fiscal balance as a percent of GDP. When this figure is above (below) one standard deviation relative to its history on an expanding basis, I define fiscal policy to be tight/contractionary (loose/expansionary). This represents the shorter-term policy stance in the style of Darrat (1990); note that the use of the primary fiscal balance as a percent of GDP or the automatic stabilizer-adjusted budget as a percent of GDP lead to substantially the same conclusions, though the former is less lagged and model-dependent than the latter, making it more suitable for use in my work. Next, I run rolling 15-year[15] quarterly regressions of the following form:

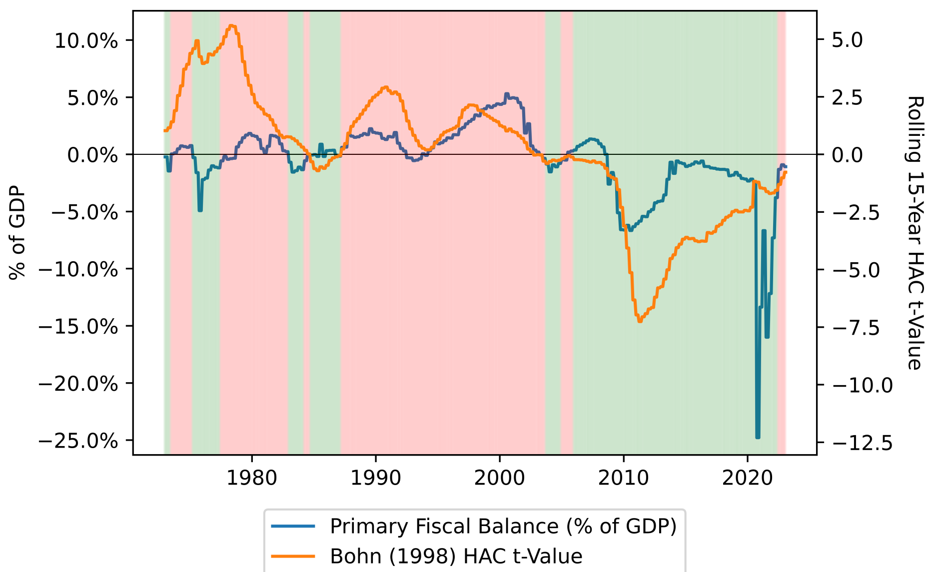
$$s_t = \rho d_t + \alpha Z_t + \varepsilon_t \tag{6}$$

Here, s_t is the primary fiscal balance as a percent of GDP, d is the beginning-of-period public debt-to-GDP, and Z_t are control variables that account for the business cycle, including the quarter-over-quarter change in the industrial production index and the U-3 unemployment rate. For the remaining periods not yet classified using the shorter-term measure, where the coefficient ρ is positive (negative) and significant, I define fiscal policy to be tight (loose), in the sense that a positive value suggests the government is intertemporally constraining itself in a Ricardian way, while a negative coefficient implies an increasing primary deficit with respect to debt, both as a percentage of GDP. Note that I utilize the heteroskedasticity and autocorrelation consistent ("HAC") standard errors of Newey and West (1987) to determine statistical significance in equation 6.

For the remaining periods still not yet classified by either the short-term shocks following Darrat (1990) or the medium-term classification following Bohn (1998), I apply the "policymakers' criterion" of Mauro, Romeu, Binder, and Zaman (2015), a test similar to the "primary gap" concept of Blanchard (1990). Specifically, I examine the following:

[15] Mauro, Romeu, Binder, and Zaman (2015) use rolling 25-year regressions with annual data. Since I use quarterly data, I shorten the length of the rolling window to better test the more medium-term fiscal stance while still using more than twice as much data in each regression. The policy classification is not sensitive to small changes in the length of the rolling window.

Figure 2: Select Fiscal Policy Variables and Regimes



This figure graphs two of the primary fiscal policy variables that are used in classifying the policy's stance as either expansionary, highlighted in green, or contractionary, highlighted in red. The primary fiscal balance as a percent of GDP is on the LHS axis, while the Bohn (1998) HAC t-value measure is on the RHS axis. December 1972 to December 2022.

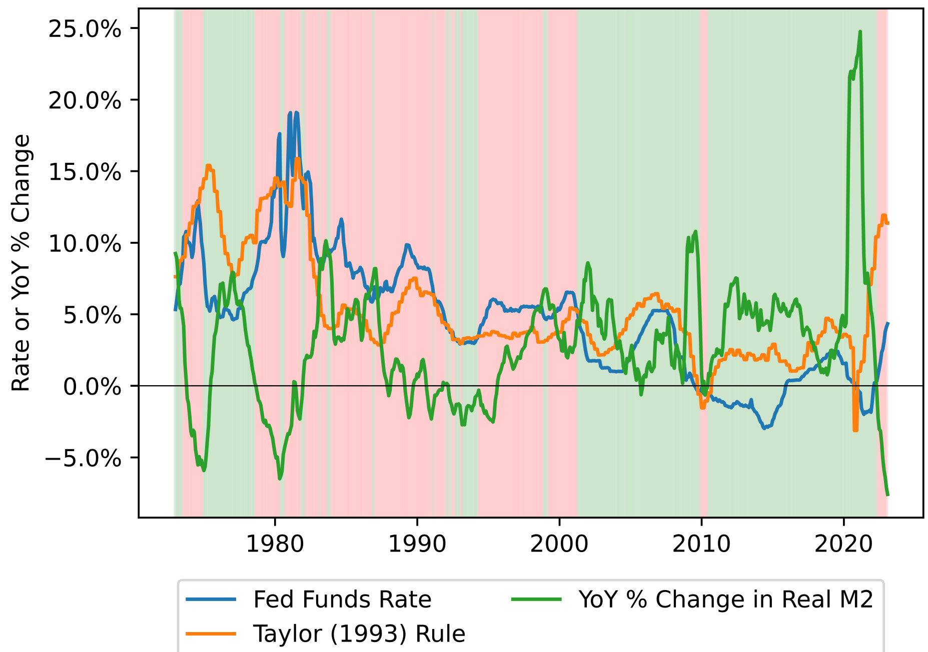
$$\rho > d_{t-1}\frac{r_t - g_t}{1 + r_t} \tag{7}$$

Here, r_t is the interest rate on debt, which I define as the 3-month Treasury bill rate, and g_t is the GDP growth rate over the trailing year. Where ρ satisfies equation 7, implying a stationary debt ratio, I define fiscal policy to be tight, and oppositely to be loose when ρ is below the quantity on the right-hand side.

Figure 2 depicts the two primary fiscal policy variables that I use to classify its stance as either expansionary or contractionary. The green shaded periods indicate loose policy, while the red shaded periods indicate tight policy.

Monetary Policy With respect to monetary policy, I apply the approach of Banerjee, Boctor, Mehrotra, and Zampolli (2022). Their primary measure of monetary policy uses the central bank independence index of Romelli (2022) across countries, but as an alternative they show that applying the Taylor (1993) rule leads to substantially similar results in their quantile regressions on forward inflation. Therefore, I first define monetary policy to be loose (tight) when the Fed Funds rate, adjusted for the Wu and Xia (2016) shadow rate, is below (above) the Taylor (1993) rule. I augment this measure with a shorter-term shock concept similar to that of fiscal policy. Namely, if the following conditions hold, I define monetary policy to be expansionary (contractionary): 1) real M2

Figure 3: Select Monetary Policy Variables and Regimes



This figure graphs three of the primary monetary policy variables that are used in classifying the policy's stance as either expansionary, highlighted in green, or contractionary, highlighted in red. December 1972 to December 2022.

money growth is expanding (contracting) on a YoY basis; 2) real M2 money growth is above (below) one standard deviation relative to its expanding mean on a YoY basis; 3) real M2 money growth is above (below) real GDP growth on a YoY basis; and 4) the last Federal Funds rate target change made by the FOMC was a decrease (increase). Taken together, this combination of expanding (contracting) money supply with the last change in the target Fed Funds rate signifies a meaningful change in the policy stance, even if the Fed Funds rate has not yet crossed the Taylor (1993) rule threshold.

A perfect example of the necessity of this short-term override is in the year 2022. In that year, the FOMC increased its target Federal Funds rate at one of the fastest clips in the prior five decades, and the real M2 money supply had fallen by over 5% on a YoY basis as of December 2022, one of the largest decreases in the series' history. Despite this obviously contractionary stance, the target Fed Funds rate was still well below the Taylor (1993) recommended policy rate level, a clear mismatch in the intentions of the FOMC compared with the current absolute level of the Fed Funds rate. Figure 3 depicts three of the primary monetary policy variables that are used to define its stance as either expansionary or contractionary.

Together, the fiscal and monetary policy regimes combine to denote 245 months of fiscal loose and monetary loose, 46 months of fiscal loose and monetary tight, 92 months of fiscal tight and monetary loose, and 218 months of fiscal tight and monetary tight joint regimes. These comprise 40.8%, 7.7%, 15.3%, and 36.3% of the time, respectively, from December 1972 to December 2022. From these joint regimes, I conclude that periods of coordinated policies are much more common than periods of uncoordinated policies.

Robustness Check As a robustness check to confirm the validity of the joint regimes defined previously, I apply the work of Kinlaw, Kritzman, and Turkington (2021). They use the Mahalanobis distance of Mahalanobis (1936), which summarizes information about similarity and distance in a single number, to develop a new probabilistic index of the business cycle called the "KKT" index. For my purposes, I include the following variables that collectively define the fiscal and monetary policy regimes:

1. Federal Funds rate, adjusted for the Wu and Xia (2016) shadow rate.
2. Federal Funds rate minus the Taylor (1993) rule.
3. YoY growth in real M2 money stock.
4. YoY growth in real M2 money stock minus YoY growth in real GDP.
5. Primary fiscal balance as a percent of GDP.
6. Public debt as a percent of GDP.
7. HAC t-value of the ρ coefficient from the rolling 15-year regressions in equation 6.
8. Continuous policymakers' criterion test from equation 7.

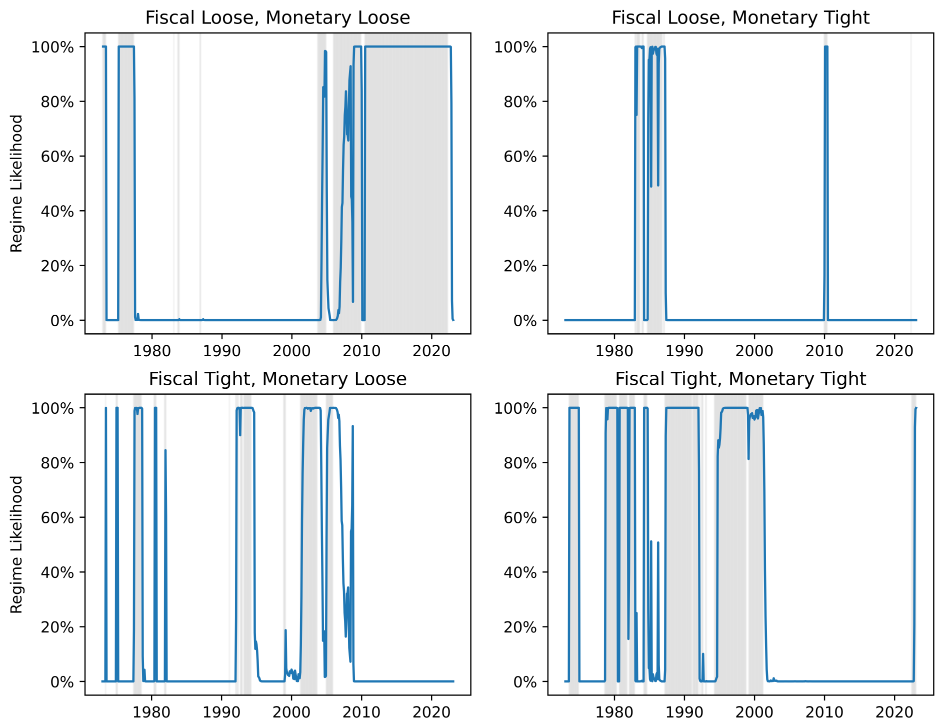
Taken together, I define these variables to represent fiscal and monetary policy jointly ("policy variables"). Then, on an expanding basis, I calculate the Mahalanobis distance of the vector of current observations, x, for the policy variables to the sub-sample of each joint regime as follows, using the example of the fiscal loose and monetary tight regime, $F_L M_T$ (all regimes are similarly defined):

$$d_{F_L M_T}(x) = (x - \mu_{F_L M_T})\Sigma^{-1}_{F_L M_T}(x - \mu_{F_L M_T})' \tag{8}$$

Here, $d_{F_L M_T}$ is the Mahalanobis distance of x with respect to the $F_L M_T$ sub-sample, $\mu_{F_L M_T}$ is a vector of the average values of the variables in the $F_L M_T$ sub-sample, and $\Sigma^{-1}_{F_L M_T}$ is the inverse of the nearest positive (semi-) definite covariance matrix[16] of the variables in the $F_L M_T$ sub-sample. The interpretation of equation 8 is that I am seeking to determine if the current observations of the

[16] statsmodels.stats.correlation_tools.cov_nearest. `https://www.statsmodels.org/dev/generated/statsmodels.stats.correlation_tools.cov_nearest.html`

Figure 4: Mahalanobis Likelihood of Joint Fiscal and Monetary Policy Regimes



This figure depicts the Mahalanobis likelihood of each joint fiscal and monetary policy regime, derived using the approach of Kinlaw, Kritzman, and Turkington (2021). The grey shaded regions represent the binary regimes as identified by the methodologies discussed in this section, while the blue lines indicate the probability of being in each regime over time. December 1972 to December 2022.

policy variables are more associated with the past values of those policy variables during the F_LM_T regime compared with the same calculation for the other regimes. I then convert each Mahalanobis distance into a likelihood, $\xi_{F_LM_T}$, using the multivariate normal PDF, and rescale each likelihood by the sum of the likelihoods of all four regimes at each date:

$$\xi_{F_LM_T}(d_{F_LM_T}) = (det(2\pi\Sigma_{F_LM_T}))^{-1/2}e^{-d_{F_LM_T}/2} \tag{9}$$

$$p_{F_LM_T} = \frac{\xi_{F_LM_T}}{\xi_{F_LM_L} + \xi_{F_LM_T} + \xi_{F_TM_L} + \xi_{F_TM_T}} \tag{10}$$

In equation 9, det is the matrix determinant, and e is the base of the natural logarithm. The probability, $p_{F_LM_T}$, in equation 10 is interpreted as the likelihood, in probability space, of being in the F_LM_T regime, and is similarly defined for the other three regimes. Figure 4 depicts the output of this analysis, and shows that the statistical approach of Kinlaw, Kritzman, and Turkington (2021) closely matches the transparent and parsimonious regimes that I define in this section, therefore serving as a useful robustness check.

I note that the inclusion of this Mahalanobis likelihood provides a second avenue through which to classify fiscal and monetary policy joint regimes. The first possibility is to use the binary regime definitions proposed previously, while the second is to identify regimes when the Mahalanobis likelihood is above 50% for a particular joint regime. I note here that the results are materially the same for either definition across the analyses that I perform, adding robustness to my results.

3.2.3 Monthly Analyses

I begin by examining the distributions of trailing and forward value factor returns and their decompositions in each regime and in the full sample from December 1972 to December 2022. In addition to simple summary statistics, I evaluate each factor's distribution within each regime sub-sample compared to the other regimes and the full sample using both the Cramer-von Mises ("CvM") and Kolmogorov-Smirnov ("K-S") non-parametric two sample tests, following Anderson (1962) and Hodges (1958), respectively. The K-S two sample test statistic, for example, between the $F_L M_T$ regime and the non-$F_L M_T$ full sample is given by:

$$D_{i,n,m} = \sup_x |F_{i,F_L M_T,n}(x) - F_{i,FS,m}(x)| \tag{11}$$

In equation 11, $F_{i,F_L M_T,n}$ and $F_{i,FS,m}$ are the empirical distribution functions of value factor i's forward one-month returns in the $F_L M_T$ regime and the non-$F_L M_T$ full sample, respectively, and n and m are the sample sizes of those sub-samples, respectively. Then, the null hypothesis that the two sub-samples are drawn from the same distribution is rejected at the α level in the scenario when:

$$D_{i,n,m} > \sqrt{-ln(\frac{\alpha}{2}) \cdot \frac{1 + \frac{m}{n}}{2m}} \tag{12}$$

These tests, in addition to comparing the first two moments (namely, returns and volatility) of value factor distributions across regimes, present a more holistic assessment of whether the data-generating process is in some ways distinct within the joint fiscal and monetary policy occurrences.

I additionally consider regressions of various specifications. In a paper reviewing the long-run returns to equities and the value factor, Asness (2021) proposes the following regression to estimate long-run factor return premiums in the context of valuation changes using rolling 12-month returns:

$$r_{i,t-12,t} = \alpha_i + \beta_i \Delta Value\ Spread_{i,t-12,t} + \varepsilon_{i,t-12,t} \tag{13}$$

Here, α_i is the long-run premium to value factor i, while any return due to changes in the relative valuation of the value versus growth sub-portfolios is accounted for in the β_i exposure. I modify Asness (2021) to incorporate the joint regime variables for fiscal and monetary policy, selecting the

$F_L M_L$ regime as the default, since it is the one that has prevailed for most of the past two decades. Specifically, I consider the following two random effects panel regressions:

$$\begin{aligned} r_{i,t-12,t} = {} & \alpha + \beta_{1,i} \Delta Value\ Spread_{t-12,t} + \beta_{2,i} (F_L M_T)_{t-12} \\ & + \beta_{3,i} (F_T M_L)_{t-12} + \beta_{4,i} (F_T M_T)_{t-12} \\ & + c_i + \varepsilon_{i,t-12,t} \end{aligned} \tag{14}$$

$$\begin{aligned} r_{i,t-12,t} = {} & \alpha + \beta_{1,i} \Delta Value\ Spread_{i,t-12,t} + \beta_{2,i} (F_L M_T)_{t-12} \\ & + \beta_{3,i} (F_T M_L)_{t-12} + \beta_{4,i} (F_T M_T)_{t-12} \\ & + \beta_{5,i} \Delta Value\ Spread_{i,t-12,t} (F_L M_T)_{t-12} \\ & + \beta_{6,i} \Delta Value\ Spread_{i,t-12,t} (F_T M_L)_{t-12} \\ & + \beta_{7,i} \Delta Value\ Spread_{i,t-12,t} (F_T M_T)_{t-12} \\ & + c_i + \varepsilon_{i,t-12,t} \end{aligned} \tag{15}$$

Equation 14 assesses whether returns on a trailing 12-month basis are different by regime compared with the $F_L M_L$ regime, controlling for valuation changes, while equation 15 evaluates whether both returns and valuation changes on a trailing 12-month basis are different by regime compared with the $F_L M_L$ regime.

The regressions in equations 14 and 15 are backward-looking and explanatory in nature. Since part of my interest is evaluating whether the information contained in fiscal and monetary policy is useful in constructing a factor timing strategy, I also examine regressions on a forward-looking basis. Fama and French (1988) and Campbell and Shiller (1988), among others, show that longer-horizon regressions of some fundamental or macroeconomic characteristic on forward returns are more predictive than at shorter horizons. I make use of this concept, appropriately adjusting standard errors for the Newey and West (1987) robust estimator, and run random effects panel regressions of the following form, where n is the number of months forward:

$$r_{i,t,t+n} = \alpha + \beta_{1,i} Value\ Spread_{i,t} + \beta_{2,i} (F_L M_T)_t + \beta_{3,i} (F_T M_L)_t + \beta_{4,i} (F_T M_T)_t + c_i + \varepsilon_{i,t,t+n} \tag{16}$$

As discussed in the Daily Event Study section, I similarly test for equations 14, 15, and 16 whether an entity fixed effects or random effects panel regression is more appropriate using the Durbin-Wu-Hausman test, but generally do not reject the null hypothesis in favor of an entity fixed effects model. I also similarly examine not only the full set of 768 value factors, but subsets of them

Table 3: Equation 5 Random Effects Panel Regression Results on FOMC Meeting Dates

		Signal Group				
	All Factors	Balance Sheet	Enterprise Value	Earnings	Cash Flow	Yield
α	0.000	0.000	0.000	0.000	0.000	-0.001^{*}
	(-0.891)	(-0.631)	(-0.746)	(-0.664)	(-0.718)	(-1.959)
$\beta_{e,i}$	-0.301^{*}	-0.406^{**}	-0.254	-0.355^{*}	-0.410^{**}	-0.114
	(-1.852)	(-2.200)	(-1.247)	(-1.801)	(-2.129)	(-1.077)
$\beta_{u,i}$	-0.557	-1.143^{**}	-0.578	-0.232	-0.366	-0.505^{*}
	(-1.382)	(-2.265)	(-1.059)	(-0.414)	(-0.900)	(-1.689)
F p-Value	0.061^{*}	0.028^{**}	0.161	0.189	0.060^{*}	0.138
R^2 Within	1.2%	2.8%	0.9%	1.2%	2.1%	0.5%

Newey and West (1987) heteroskedasticity and autocorrelation consistent t-statistics in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table presents equation 5 random effects panel regression results for all 768 value factors on FOMC meeting dates, as well as value factors grouped by signal group as documented in table 1. December 1988 to December 2022, not inclusive of ZLB periods.

for each panel regression based on signal group, signal, size, value, weight, and sector.

4 Results

4.1 Daily Results

Regardless of the control variables included in equation, 5, the results I find for the Bernanke and Kuttner (2005) FOMC announcement day regressions are materially the same (and the control variables are generally insignificant). As such, I focus on the results for equation 5 specifically. Table 3 presents the results of the random effects panel regressions specified by equation 5.

At the aggregate level of all value factors, there appears to be little impact of monetary policy announcements on FOMC meeting days on total returns, even when controlling for several other fiscal and monetary policy related variables, such as the Baker, Bloom, and Davis (2016) EPU index. However, when examined by signal group, table 3 suggests that the balance sheet factors are in fact impacted by both the expected and unexpected components of Fed Funds target rate changes made by the FOMC. What explains the concentration of significant results in this particular signal grouping? The balance sheet factors tend to be the most highly levered on a debt-to-market equity ("D/E") basis in the December 1988 period onwards. For example, aggregating all underlying factors' full sample D/E ratios, calculated as the difference between the long and short sub-portfolio D/E ratios, reveals that the balance sheet factors have on average 1.4x more turns of leverage in the long sub-portfolio versus the short sub-portfolio over this time period. This compares with -0.2x for the enterprise value factors, 0.2x for the earnings factors, 0.2x for the cash flow factors, and 0.7x for the yield factors. This implies that (surprise) decreases in interest rates, operating through the cash flow duration channel given the importance of nearer-term cash flows for more highly levered firms relative to less levered firms, as shown by Gormsen and Lazarus (2019), are net positive (negative) for the value factor in the short-run when rates decrease (increase). Value firms benefit on a relative basis to growth firms when the Fed Funds rate is decreased, as they may have the opportunity to refinance their heavier debt loads at a lower rate. Oppositely when rates rise, value firms' higher leverage is a net detractor relative to growth firms. These results match those of Ippolito and Ozdagli (2018), who argue that financially constrained firms have greater sensitivity to monetary policy.

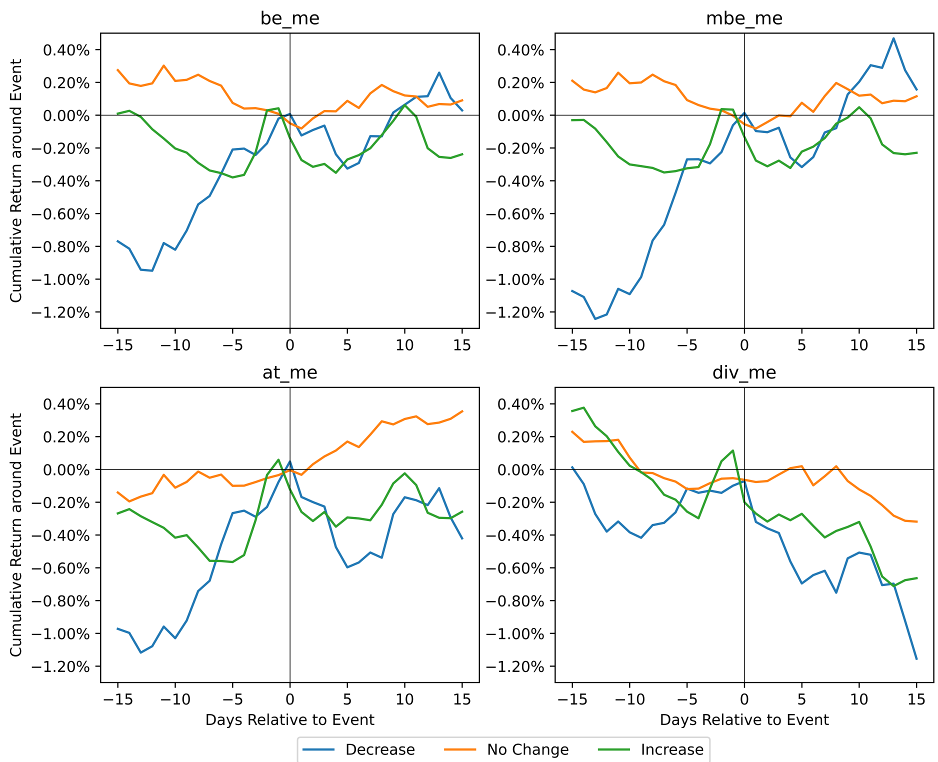
The effect of Fed Funds rate changes on the balance sheet value factors is primarily seen prior to and on FOMC meeting dates when the ultimate policy action is a rate decrease. Using the event study methodology and examining the period from 15 days prior to 15 days after each announcement, for example, I find that the balance sheet factors, which include the book-to-market equity, be_me, modified book-to-market equity, mbe_me, and assets-to-market equity, at_me, factors, all experience positive returns heading into FOMC meeting dates when the ultimate policy decision is a rate decrease. This compares with those factors on periods when the policy decision is either no change or an increase, around which the balance sheet factors display no material pre- or post-announcement reaction or drift. Compared with other factors, for example the dividend yield, div_me, factors, this result is highly distinct and emphasizes that it is primarily rate decreases that benefit those value factors that tend to be most highly levered on a net basis in the post-December 1988 period. Figure 5 plots the event study cumulative abnormal returns around each FOMC announcement date for the previously mentioned factors aggregated at the signal level.

Overall, though some results appear worthy of further investigation, I conclude that the value factor as an overall concept does not necessarily respond to specific changes in monetary policy in the short-term, even when controlling for fiscal policy using the Baker, Bloom, and Davis (2016) EPU index. The balance sheet factors are the one signal group category that, due to their markedly higher net leverage at the sub-portfolio level, experience some impact of monetary policy specifically around FOMC meeting announcement dates. I therefore move to the monthly results, which test for fiscal and monetary policy impacts on the value factor's decomposed returns over the medium- to longer-term, the primary focus of my paper.

4.2 Monthly Results

I first examine the results of the CvM and K-S non-parametric two sample test results pertaining to each factor's forward 1-month returns within each regime and the full sample. Table 4 presents the proportion of factors within each grouping category for which I rejected the null hypothesis that the two different regime sub-samples are drawn from the same distribution. Unlike the Kullback–Leibler divergence, which is not symmetric, both the CvM and K-S non-parametric two sample tests are

Figure 5: Event Study of Cumulative Abnormal Returns after FOMC Meetings by Policy Action



This figure plots pre- and post-announcement cumulative abnormal returns for book-to-market equity, be_me, modified book-to-market equity, mbe_me, assets-to-market equity, at_me, and dividend yield, div_me, value factors. Value factor returns around FOMC announcement dates are first aggregated by signal and by type of announcement, namely no rate change, a rate decrease, and a rate increase. Abnormal returns are calculated as cumulative relative to the beginning of the event date; for example, the ∼-1% return on day -15 for the at_me factor for rate decreases indicates that the abnormal cumulative average return to all at_me factors for rate decreases is ∼1% from day -15 to day 0, while the the ∼0.4% return on day 15 for the at_me factors after no Fed Funds target change indicates that the abnormal cumulative average return to all at_me factors for no rate changes is ∼0.4% from day 0 (the beginning of the announcement date) to day 15. December 1988 to December 2022, not inclusive of ZLB periods.

Table 4: CvM Non-Parametric Two Sample Test Rejection Proportions by Joint Regime

		$F_L M_L$				$F_L M_T$			$F_T M_L$		$F_T M_T$
Design Choice	Category	$F_L M_T$	$F_T M_L$	$F_T M_T$	FS	$F_T M_L$	$F_T M_T$	FS	$F_T M_T$	FS	FS
Signal Group	Balance Sheet	4.9%	18.8%	0.7%	6.9%	0.0%	0.7%	1.4%	13.2%	12.5%	1.4%
Signal Group	Enterprise Value	12.0%	37.5%	2.6%	16.7%	0.5%	3.6%	2.1%	24.5%	27.1%	4.7%
Signal Group	Earnings	28.6%	16.1%	22.4%	35.4%	0.5%	2.1%	4.2%	0.0%	3.1%	2.6%
Signal Group	Cash Flow	33.3%	65.6%	20.8%	60.4%	4.2%	5.2%	6.3%	8.3%	27.1%	1.0%
Signal Group	Yield	6.9%	6.3%	13.2%	9.0%	9.0%	3.5%	4.9%	0.0%	1.4%	6.9%
Size	All	20.3%	25.5%	10.9%	21.9%	3.1%	4.7%	3.6%	13.0%	15.6%	3.6%
Size	Mega	10.4%	15.1%	5.2%	9.4%	3.1%	3.1%	4.2%	10.4%	10.9%	4.7%
Size	Large	8.3%	27.1%	6.3%	17.7%	2.6%	3.1%	4.2%	10.9%	16.1%	3.1%
Size	Small	27.1%	37.5%	23.4%	45.3%	1.0%	0.5%	2.1%	4.2%	11.5%	2.6%
Value	Deep	17.2%	34.8%	15.2%	29.7%	2.3%	2.3%	3.1%	12.1%	18.0%	3.9%
Value	Moderate	17.6%	23.0%	10.5%	24.2%	1.2%	3.1%	3.5%	8.2%	11.3%	3.5%
Value	Shallow	14.8%	21.1%	8.6%	16.8%	3.9%	3.1%	3.9%	8.6%	11.3%	3.1%
Weight	VW	12.0%	21.6%	10.4%	18.5%	1.6%	3.1%	3.4%	8.1%	12.0%	4.4%
Weight	EW	21.1%	31.0%	12.5%	28.6%	3.4%	2.6%	3.6%	11.2%	15.1%	2.6%
Sector	SA	9.4%	33.9%	9.1%	19.8%	1.8%	1.3%	0.5%	15.6%	23.7%	4.9%
Sector	SN	23.7%	18.8%	13.8%	27.3%	3.1%	4.4%	6.5%	3.6%	3.4%	2.1%
All Factors		16.5%	26.3%	11.5%	23.6%	2.5%	2.9%	3.5%	9.6%	13.5%	3.5%

This table documents the proportion of value factors within each portfolio construction design choice grouping whose forward 1-month total return distributions in both regimes were statistically determined to have been drawn from a different distribution by the rejection of the CvM non-parametric two sample test null hypothesis at the 95% confidence level. The first distribution is the one above, while the second one being compared is the one below the line. "FS" stands for full sample and references the entire full sample distribution holding out the first comparison regime. December 1972 to December 2022.

bidirectionally equivalent, so I present each unique combination of joint regimes and the full sample. Since the results of the two tests are materially the same across all joint regime comparisons, emphasizing the robustness of the results, I also specifically focus on the CvM tests for parsimony.

Table 4 shows that the $F_L M_L$ regime is the one across value factors for which the distribution of their returns is most likely to be statistically drawn from a different distribution than other regimes at the forward 1-month horizon. This result is highly robust and consistent across different signal groups, as well as value factor sizes, breakpoints, sub-portfolio weightings, and sector schemes. For example, across all value factors, 23.6% of them have forward 1-month total return distributions that are drawn from a different distribution in the $F_L M_L$ regime compared to the remaining full sample period based on the CvM non-parametric two sample test. Since we would expect only a 5% proportion simply by chance, results that indicate a materially higher proportion than this are strongly indicative of differences in the return generation process between joint regimes.

Within the $F_L M_L$ comparisons, the enterprise value, earnings, and cash flow factors appear to be most statistically distinct from one another and relative to the full sample. The significant results are also concentrated within the small, deep, equal-weighted value factors. Though I will specifically examine the forward structural and revaluation returns across each regime and in the full sample later in this paper, one way to see why these return distributions may be different from one another is to examine the difference between various fundamental characteristics of each value factor

Table 5: Select Fundamental Characteristics of Six Small, Deep, Equal-Weighted Value Factors by Signal Group for Each Joint Policy Regime

Signal Group	Size	Value	Weight	Joint Regime	D/E	ROIC	ROA	ROE	*Value Spread*
Balance Sheet	Small	Deep	EW	$F_L M_L$	3.34x	14.9%	-11.6%	-3.3%	7.16x
Balance Sheet	Small	Deep	EW	$F_L M_T$	2.92x	-10.2%	-6.1%	-9.9%	7.43x
Balance Sheet	Small	Deep	EW	$F_T M_L$	2.27x	-9.0%	-13.8%	-11.8%	8.07x
Balance Sheet	Small	Deep	EW	$F_T M_T$	2.44x	-6.6%	-32.0%	0.0%	7.88x
Enterprise Value	Small	Deep	EW	$F_L M_L$	-0.44x	63.0%	19.9%	60.4%	2.60x
Enterprise Value	Small	Deep	EW	$F_L M_T$	-0.53x	16.5%	7.2%	21.7%	2.02x
Enterprise Value	Small	Deep	EW	$F_T M_L$	-0.24x	20.9%	14.1%	34.8%	2.36x
Enterprise Value	Small	Deep	EW	$F_T M_T$	-0.12x	19.6%	2.8%	39.6%	2.67x
Earnings	Small	Deep	EW	$F_L M_L$	-1.32x	53.5%	27.8%	103.9%	1.54x
Earnings	Small	Deep	EW	$F_L M_T$	-2.54x	22.1%	14.1%	40.5%	1.14x
Earnings	Small	Deep	EW	$F_T M_L$	0.19x	23.0%	38.5%	59.6%	1.46x
Earnings	Small	Deep	EW	$F_T M_T$	0.53x	21.7%	31.7%	71.1%	1.93x
Cash Flow	Small	Deep	EW	$F_L M_L$	0.08x	26.7%	20.4%	54.4%	1.76x
Cash Flow	Small	Deep	EW	$F_L M_T$	-1.69x	6.7%	4.1%	6.9%	1.15x
Cash Flow	Small	Deep	EW	$F_T M_L$	-0.13x	14.3%	18.6%	32.9%	1.37x
Cash Flow	Small	Deep	EW	$F_T M_T$	-0.47x	11.7%	10.6%	25.1%	1.35x
Yield	Small	Deep	EW	$F_L M_L$	2.49x	13.3%	0.3%	2.7%	1.43x
Yield	Small	Deep	EW	$F_L M_T$	3.29x	-1.7%	-1.4%	-1.5%	2.04x
Yield	Small	Deep	EW	$F_T M_L$	0.41x	0.9%	-12.6%	2.3%	1.55x
Yield	Small	Deep	EW	$F_T M_T$	0.76x	0.8%	-36.8%	1.4%	1.91x

This table presents select average fundamental characteristic measures of all value factors aggregated by signal group for the small, deep, equal-weighted value factors. For example, the 14.9% ROIC for the balance sheet grouping within the $F_L M_L$ regime indicates that during the $F_L M_L$ joint policy regime, those six factors on average had returns on invested capital that were 14.9% higher in the long sub-portfolio than in the short sub-portfolio on a weighted average basis across all six of those factors. Measure definitions are based on those formulated by Jensen, Kelly, and Pedersen (2021). December 1972 to December 2022.

portfolio in each regime. Table 5 presents these averages of select relative fundamental characteristics aggregated by signal group for the six small, deep, equal-weighted value factors within each signal group.

For the enterprise value, earnings, and cash flow factors, the ROIC, ROA, and ROE efficiency measures, which are calculated as the difference between the weighted average long sub-portfolio characteristic value and the weighted average short sub-portfolio characteristic value, tend to be highest during the $F_L M_L$ joint policy regime, and oppositely lowest during the $F_L M_T$ joint regime. For the enterprise value and earnings factors more specifically, the D/E ratios are lower when fiscal policy is loose and higher when fiscal policy is tight. Indeed, for the earnings factors, the long sub-portfolios have higher D/E ratios on a weighted average basis than the short sub-portfolios when fiscal policy is tight, while the opposite is true when fiscal policy is loose. The relative valuation between the long and short sub-portfolios, $Value\ Spread$, does not appear to show any consistently meaningful difference across regimes for any of the factors, with the possible exception that the highest relative valuation spreads for the enterprise value and earnings factors tend to occur on average when fiscal and monetary policy are coordinated, the two most common joint regimes.

Table 6: Equation 15 Random Effects Panel Regression Results by Signal Group

	All Factors	Signal Group: Balance Sheet	Enterprise Value	Earnings	Cash Flow	Yield
α	0.031	0.068	0.043	0.011	0.025	0.018
	(0.597)	(1.220)	(0.891)	(0.225)	(0.618)	(0.663)
$\Delta Value\ Spread_{t-12,t}$	-0.273^{***}	-0.645^{***}	-0.312^{***}	-0.104^{**}	-0.280^{***}	-0.284^{***}
	(−8.723)	(−11.716)	(−6.545)	(−1.967)	(−5.522)	(−8.525)
$(F_L M_T)_{t-12}$	0.050^{***}	0.011	0.070^{***}	0.072^{*}	0.048^{***}	0.015
	(2.394)	(0.535)	(3.199)	(1.658)	(2.894)	(0.956)
$(F_T M_L)_{t-12}$	0.073^{***}	0.043^{*}	0.097^{***}	0.105^{***}	0.086^{***}	0.009
	(3.200)	(1.713)	(3.565)	(3.895)	(3.065)	(0.527)
$(F_T M_T)_{t-12}$	0.034^{*}	0.007	0.047^{**}	0.060^{***}	0.044^{***}	−0.006
	(1.905)	(0.412)	(2.180)	(2.408)	(2.402)	(−0.491)
$\Delta Value\ Spread_{t-12,t}(F_L M_T)_{t-12}$	0.061	0.169	0.060	−0.045	0.268^{***}	0.036
	(1.233)	(1.574)	(0.638)	(−0.507)	(3.906)	(0.441)
$\Delta Value\ Spread_{t-12,t}(F_T M_L)_{t-12}$	−0.083	0.194^{**}	−0.114	-0.227^{***}	0.023	−0.019
	(−1.180)	(2.199)	(−1.247)	(−2.841)	(0.227)	(−0.301)
$\Delta Value\ Spread_{t-12,t}(F_T M_T)_{t-12}$	-0.284^{***}	−0.111	-0.387^{***}	-0.369^{***}	−0.128	-0.174^{***}
	(−2.582)	(−1.040)	(−2.736)	(−3.123)	(−1.105)	(−2.382)
F p-Value	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
R^2 Within	35.8%	45.4%	45.1%	33.7%	31.8%	33.9%

Newey and West (1987) heteroskedasticity and autocorrelation consistent t-statistics in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table presents equation 15 random effects panel regression results for all 768 value factors on FOMC meeting dates, as well as value factors grouped by signal group as documented in table 1. December 1972 to December 2022.

Although I do not directly discuss each individual result, as such an exercise is too large to be given appropriate ink across the 768 factors that I form, table 5 suggests one possible avenue through which the statistical difference in the distributions of forward 1-month total returns by regime can be explained, namely through the use of various fundamental characteristics. The results suggest a clear differentiation between the nature of value factor portfolios across regimes for the small, deep, equal-weighted factors aggregated by signal groups that indicated the highest proportion of statistically different return distributions by joint policy regime. I leave further exploration of this type of analysis to future work.

To more directly examine the drivers of performance across each regime, and therefore to provide an explanatory account of the results from table 4, I turn to the Asness (2021) regressions formulated in random effects panel regression equations 14 and 15. For the sake of parsimony, I primarily focus on results for equation 15. Table 6 presents such results across all factors and by signal group.

The results in table 6 clearly indicate that the enterprise value, earnings, and cash flow factors in particular experience statistically significantly higher returns during the non-$F_L M_L$ regime than in the $F_L M_L$ regime. This result holds somewhat more weakly across all factors, but indicates that the CvM distributional results were suggestive of a difference at minimum in the level of returns during each regime. As expected, given the CvM results, the balance sheet and yield factors appear to respond less to changes in the fiscal and monetary policy joint regime in the Asness (2021) regression specification, as average returns in each non-$F_L M_L$ regime, shown by the binary variables, are generally not statistically different from the returns of these factors during the $F_L M_L$ regime.

Beyond simply the average returns to each factor during each regime indicated by the binary variables, the interaction variables between changes in the $Value\ Spread$ of each factor and the binary regime variables also suggest a difference in the return generating process across joint regimes. For example, the $F_T M_T$ regime shows that all factors, but in particular the enterprise value, earnings, and yield factors, all experience a greater sensitivity to changes in relative valuations between the long and short factor sub-portfolios than in the baseline $F_L M_L$ regime. Indeed, while a 1% increase in the relative valuation spread, suggestive of growth benefiting relative to value as documented in equation 2, leads to a -0.273% change in all factors' total returns on average from $t-12$ to t, during the $F_T M_T$ regime this sensitivity increases to a -0.557% change. The wedge, as Ilmanen, Nielsen, and Chandra (2015) term it, between changes in valuations and realized returns between rebalancing dates, is smaller during the latter regime than during the former. The CvM test results from table 4, while possibly explained by differences fundamental characteristics as demonstrated by their bifurcation across joint policy regimes in table 5 for select factors, are clearly also driven at least in part by changes in the sensitivity of each value factor's total return to changes in its relative valuation spread.

As a robustness check, table 7 presents the same results as table 6, except that this time, the random effects panel regressions of equation 15 are applied to value factors grouped by size and value, rather than signal group. As with table 6, the results indicate that average trailing 12-month returns during non-$F_L M_L$ regimes are statistically higher than those returns during the $F_L M_L$ regime. Indeed, as confirmed by table 6 as well, such returns during the $F_L M_L$ regime are actually not even statistically different from zero, suggesting that on a total basis, value factor returns during periods when both fiscal and monetary policy are loose is structurally zero, and only driven by changes in the $Value\ Spread$.

In line with the CvM non-parametric two sample test results of table 4, the results in table 7 also suggest that small cap value factors are more impacted than mega or large cap factors in both their average level of returns and sensitivity to relative valuation spread changes during non-$F_L M_L$ regimes than in the baseline joint regime that has primarily prevailed for most of the past two decades. Oppositely, mega cap value factors do not appear to be particularly responsive to fiscal and monetary policy. This confirms the work of Asness, Frazzini, Israel, and Moskowitz (2015), who find that the large cap HML factor does not have statistically significantly positive out-of-sample returns despite the original HML factor of Fama and French (1993) having such positive returns. Lastly, across many of the random effects panel regression groupings, the sensitivity of total returns to changes in relative valuations is strongest during the $F_T M_T$ regime relative to other regimes, the diametrically opposed joint policy classification period to the baseline. Revaluation returns appear

Table 7: Equation 15 Random Effects Panel Regression Results by Size and Value

	Size				Value		
	All	Mega	Large	Small	Deep	Moderate	Shallow
α	0.024	0.020	0.034	0.048	0.033	0.036	0.026
	(0.620)	(0.789)	(0.951)	(0.812)	(0.515)	(0.720)	(0.760)
$\Delta Value\ Spread_{t-12,t}$	-0.285^{***}	-0.274^{***}	-0.308^{***}	-0.233^{***}	-0.241^{***}	-0.323^{***}	-0.341^{***}
	(−8.178)	(−7.404)	(−7.707)	(−5.302)	(−7.108)	(−10.099)	(−10.857)
$(F_L M_T)_{t-12}$	0.046^{**}	0.030^{*}	0.044^{*}	0.078^{***}	0.070^{**}	0.045^{***}	0.033^{***}
	(2.140)	(1.660)	(1.693)	(3.405)	(2.276)	(2.404)	(2.606)
$(F_T M_L)_{t-12}$	0.059^{***}	0.051^{**}	0.085^{***}	0.099^{***}	0.104^{***}	0.064^{***}	0.040^{***}
	(3.082)	(2.210)	(3.272)	(3.385)	(3.265)	(3.125)	(3.025)
$(F_T M_T)_{t-12}$	0.028	0.017	0.041^{**}	0.050^{***}	0.044^{*}	0.035^{**}	0.026^{**}
	(1.619)	(1.010)	(2.069)	(2.357)	(1.797)	(2.075)	(2.224)
$\Delta Value\ Spread_{t-12,t}(F_L M_T)_{t-12}$	0.055	0.141^{***}	0.064	−0.006	0.073^{*}	0.048	0.048
	(0.927)	(2.931)	(1.047)	(−0.085)	(1.668)	(0.702)	(0.643)
$\Delta Value\ Spread_{t-12,t}(F_T M_L)_{t-12}$	-0.124^{*}	0.039	−0.091	-0.208^{***}	−0.061	−0.110	−0.136
	(−1.665)	(0.565)	(−0.967)	(−2.489)	(−0.982)	(−1.402)	(−1.564)
$\Delta Value\ Spread_{t-12,t}(F_T M_T)_{t-12}$	-0.280^{***}	-0.185^{*}	-0.308^{***}	-0.362^{***}	-0.236^{**}	-0.357^{***}	-0.350^{***}
	(−2.662)	(−1.795)	(−2.531)	(−2.853)	(−2.283)	(−2.974)	(−3.136)
F p-Value	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
R^2 Within	39.1%	35.8%	41.5%	30.9%	30.4%	43.6%	48.0%

Newey and West (1987) heteroskedasticity and autocorrelation consistent t-statistics in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table presents equation 15 random effects panel regression results for value factors grouped by size and value. December 1972 to December 2022.

to be strongly influencing total value factor returns based on the prevailing joint fiscal and monetary policy regime that existed at $t - 12$ on a rolling 12-month basis.

While explanatory accounts modelled by regressions of the form following Asness (2021) are no doubt important, one of my interests in this paper is to examine whether information in fiscal and monetary policy can be used to make tactical timing decisions with respect to the value factor. I explore these timing strategies in more detail in Section 5, but before that I examine more directly the forward returns to the value factor by joint policy regime as compared with the full sample. Table 8 presents forward 36-month returns to value factors aggregated by signal group, size, value, weight, and sector categories. The total return statistics are decomposed into structural and revaluation components following Arnott, Harvey, Kalesnik, and Linnainmaa (2021), as discussed in the Data and Methodology section[17]. This decomposition can be more directly used on a forward return basis to account for the sources of value's performance and with regressions in equation 16 as the level of relative valuations, rather than the change, is employed; using the change means that revaluation returns are nearly fully explained by the $\Delta Value\ Spread$ independent variable from equations 14 and 15. While the choice of 36-months forward is arbitrary, the results are materially similar when examined from between 12-60 months forward, and the forward 36-month horizon balances my desire to examine long-run horizons following Fama and French (1988) and Campbell and Shiller (1988) while maintaining the possibility of a shorter-term timing strategy based on the information contained in fiscal and monetary policy.

[17]Note: return decomposition does not hold exactly within design choice categories as the results are aggregated across factors. If one specific factor were examined, the decomposition is a mathematical identity.

Table 8: Forward 36-Month Decomposed Returns to Value Factors Aggregated by Design Choice

		Total Returns					Structural Returns					Revaluation Returns				
Design Choice	Category	FS	F_LM_L	F_LM_T	F_TM_L	F_TM_T	FS	F_LM_L	F_LM_T	F_TM_L	F_TM_T	FS	F_LM_L	F_LM_T	F_TM_L	F_TM_T
Signal Group	Balance Sheet	5.8%	3.9%	6.3%	5.1%	7.8%	6.2%	5.2%	5.0%	5.4%	7.7%	-0.1%	-1.1%	1.5%	0.1%	0.3%
Signal Group	Enterprise Value	6.3%	2.2%	8.4%	6.8%	9.0%	6.8%	4.9%	8.9%	8.5%	6.9%	0.2%	-2.0%	-0.1%	-0.9%	2.8%
Signal Group	Earnings	4.3%	0.3%	7.8%	3.7%	7.4%	3.8%	3.2%	9.2%	7.7%	1.0%	1.6%	-2.0%	-0.8%	-2.5%	7.7%
Signal Group	Cash Flow	4.2%	1.1%	5.1%	4.4%	6.6%	6.4%	1.9%	7.7%	5.5%	10.7%	-1.4%	-0.2%	-1.9%	-0.1%	-3.1%
Signal Group	Yield	1.1%	0.1%	3.2%	-0.9%	2.5%	0.6%	1.9%	1.0%	-0.1%	-0.1%	1.0%	-1.1%	2.5%	-0.3%	3.2%
Size	All	3.4%	0.9%	6.0%	3.2%	5.1%	3.5%	2.7%	6.0%	4.5%	3.2%	0.5%	-1.3%	0.3%	-0.6%	2.8%
Size	Mega	2.5%	0.5%	3.0%	3.2%	3.6%	2.8%	3.0%	5.9%	3.9%	1.4%	0.5%	-1.7%	-2.2%	0.2%	3.2%
Size	Large	5.0%	2.2%	6.8%	3.6%	7.9%	5.2%	4.4%	6.3%	6.2%	5.1%	0.5%	-1.6%	0.9%	-1.6%	3.4%
Size	Small	6.9%	2.5%	10.1%	5.9%	10.7%	7.4%	4.4%	8.4%	8.3%	9.2%	0.2%	-1.3%	2.2%	-1.6%	2.1%
Value	Deep	5.0%	1.3%	7.2%	4.7%	7.9%	5.4%	3.9%	8.7%	7.0%	5.0%	1.0%	-1.4%	-0.6%	-0.7%	4.4%
Value	Moderate	4.8%	1.9%	7.0%	4.2%	7.3%	5.0%	3.9%	6.6%	5.9%	5.2%	0.3%	-1.6%	0.7%	-1.1%	2.6%
Value	Shallow	3.5%	1.4%	5.2%	3.0%	5.3%	3.8%	3.0%	4.6%	4.2%	4.0%	0.0%	-1.4%	0.8%	-0.9%	1.6%
Weight	VW	5.2%	2.0%	6.6%	4.6%	8.1%	5.4%	4.0%	7.0%	6.2%	5.9%	0.5%	-1.4%	0.1%	-0.7%	3.0%
Weight	EW	3.7%	1.1%	6.4%	3.3%	5.6%	4.0%	3.2%	6.3%	5.2%	3.6%	0.3%	-1.5%	0.5%	-1.1%	2.8%
Sector	SA	4.5%	1.4%	6.6%	4.0%	7.1%	5.0%	4.2%	6.5%	5.8%	4.8%	0.3%	-2.1%	0.5%	-0.9%	3.1%
Sector	SN	4.4%	1.6%	6.3%	3.9%	6.6%	4.5%	2.9%	6.7%	5.6%	4.7%	0.5%	-0.8%	0.1%	-0.9%	2.6%
All Factors		4.5%	1.5%	6.5%	4.0%	6.8%	4.7%	3.6%	6.6%	5.7%	4.7%	0.4%	-1.4%	0.3%	-0.9%	2.9%

This table presents average forward 36-month returns to each value factor aggregated by signal group, size, value, weight, and sector. Total returns are decomposed into structural and revaluation components following Arnott, Harvey, Kalesnik, and Linnainmaa (2021). December 1972 to December 2022.

Table 8 shows that total returns to the value factor, however it is formulated across the five portfolio construction design choices that I explore, are higher during periods of tight policy than during periods of loose policy. This is true both with respect to fiscal and monetary policy individually, as well as in their joint regimes. Indeed, across all 768 factors, average total 36-month forward returns are 6.5% in the F_LM_T regime compared with 1.5% in the F_LM_L regime, and are 6.8% in the F_TM_T regime compared with 4.0% in the F_TM_L regime. Whenever monetary policy is classified as loose, the average total 36-month forward returns to the concept of value as a cross-sectional premium are lower than the full sample average, and oppositely when monetary policy is tight, total 36-month forward returns are higher. At this aggregate level, a result that is consistently seen regardless of the aggregation by design choice employed, it appears that monetary policy is the more important policy regime with respect to value's medium-term forward total performance.

The revaluation returns documented in table 8 show that the conclusions drawn with respect to total returns are materially the same in this portion of the decomposition. With the exception of the cash flow factors using the signal group design choice, revaluation returns are generally positive and higher than the full sample average in the F_TM_T regime compared to others, and are generally negative and lower than the full sample average in the F_LM_L regime. As with the total return results, it is also generally the case within the revaluation returns that, holding fiscal policy constant, when monetary policy is tight, revaluation returns are higher. The difference is most clear between the F_TM_T and F_TM_L regimes, at 3.8% across all factors, although it is also still present between the F_LM_T and F_LM_L regimes at 1.7%. My hypothesis in this paper is that fiscal and monetary policy primarily impact the value factor's returns through the revaluation channel, an hypothesis supported strongly by the simple forward returns summary statistics in table 8.

To support the conclusions from table 8 in a more formal way, table 9 presents the results of the equation 16 random effects panel regressions for forward 36-month total, structural, and revaluation returns across all 768 factors grouped by size. Table 10 then presents those same results for the factors grouped by signal group.

Examining the results from table 9 across all factors, it is statistically clear that total forward 36-month returns to the value factor are higher in non-$F_L M_L$ regimes, after controlling for the level of relative valuations between the long and short sub-portfolios. The regime with the highest relative returns to the $F_L M_L$ regime is the $F_L M_T$ regime, followed by the jointly tight regime. Furthermore, higher levels of relative valuations strongly imply higher forward 36-month total returns across all value factors, an unsurprising result that confirms the findings of many other papers, including Asness, Liew, Pedersen, and Thapar (2021), among others.

The surprising result from table 9, and which runs counter to my original hypothesis, is the source of the total returns identified by the random effects panel regression in column one. The revaluation return decomposition is somewhat statistically significantly positive for the non-$F_L M_L$ regimes, but is not nearly as strong as those results at the total return level. Forward 36-month revaluation returns are higher when in the $F_L M_T$ and $F_T M_T$ regimes, both of which confirm the forward return results of table 8, in that monetary policy appears to be the more important policy with respect to influencing the forward returns to the concept of the cross-sectional value premium. As with total returns, higher levels of relative valuations strongly imply higher forward 36-month revaluation returns, a result robust to any category of aggregation by size or signal group.

The driver of value factor total returns on a forward medium-term basis is therefore primarily structural return differences across regimes, in particular with respect to the baseline $F_L M_L$ joint policy regime that has prevailed for most of the past two decades. Examined from the perspective of all 768 value factors, the results are directionally and in magnitude similar to the total return results, in that average forward 36-month structural returns are highest in the $F_L M_T$ regime, followed by the jointly tight policy regime. Grouped by size, this result is most significant among the small cap value factors.

Across different size and signal group categories for which equation 16 is evaluated, the results are somewhat mixed and indicate that it is the combination of both structural and revaluation returns, which themselves are not necessarily statistically different across regimes, that contribute to differences in forward 36-month total returns to the value factor. As noted previously, the small cap value factors tend to exhibit the strongest results, confirming many prior results that I report, including in tables 4, 5, 7, and 8. Among signal groups, it is again the enterprise value, earnings, and cash flow factors that exhibit the greatest sensitivity to changes in the fiscal and monetary policy joint regime. Across these factor categories, the returns during the $F_L M_T$ regime are generally highest, followed by the $F_T M_T$ regime, a similar result to the overall results for all 768 factors. Within these categories, the strongest evidence that structural returns differ by joint policy regime

Table 9: Equation 16 Random Effects Panel Regression Results on All Decomposed Value Factor Forward 36-Month Returns by Size

	Total Returns					Structural Returns					Revaluation Returns				
		Size					Size					Size			
	All Factors	All	Mega	Large	Small	All Factors	All	Mega	Large	Small	All Factors	All	Mega	Large	Small
α	-0.081^{*}	-0.084^{**}	-0.078^{***}	-0.089^{***}	-0.070	0.114^{***}	0.096^{***}	0.121^{***}	0.112^{***}	0.119^{***}	-0.142^{***}	-0.137^{***}	-0.178^{***}	-0.146^{***}	-0.106^{***}
	(-1.784)	(-2.268)	(-2.908)	(-2.377)	(-1.384)	(4.207)	(3.635)	(5.105)	(4.283)	(3.587)	(-9.524)	(-8.394)	(-9.245)	(-8.407)	(-8.467)
$Value\ Spread_t$	0.044^{***}	0.042^{***}	0.038^{***}	0.051^{***}	0.042^{***}	-0.036^{***}	-0.032^{***}	-0.042^{***}	-0.031^{***}	-0.035^{***}	0.058^{***}	0.057^{***}	0.073^{***}	0.059^{***}	0.043^{***}
	(7.071)	(8.444)	(8.530)	(6.222)	(4.018)	(-6.553)	(-6.716)	(-7.221)	(-5.222)	(-4.947)	(18.189)	(20.089)	(22.666)	(14.280)	(14.237)
$(F_L M_T)_t$	0.057^{***}	0.058^{***}	0.037^{***}	0.056^{***}	0.076^{***}	0.024^{***}	0.028^{***}	0.020	0.010	0.040^{***}	0.028^{**}	0.026^{**}	0.020	0.037^{***}	0.034^{**}
	(4.496)	(4.659)	(3.062)	(4.254)	(5.291)	(2.636)	(3.025)	(1.570)	(1.350)	(3.325)	(2.184)	(2.068)	(1.441)	(2.788)	(2.274)
$(F_T M_L)_t$	0.029^{***}	0.027^{***}	0.032^{***}	0.020	0.037^{***}	0.018^{**}	0.015^{*}	0.000	0.020	0.038^{***}	0.010	0.010	0.03^{***}	0.010	0.000
	(2.662)	(2.647)	(3.176)	(1.497)	(2.788)	(2.249)	(1.894)	(0.327)	(1.368)	(4.267)	(1.147)	(1.324)	(2.583)	(0.472)	(-0.151)
$(F_T M_T)_t$	0.041^{***}	0.031^{**}	0.020	0.040^{***}	0.071^{***}	0.021^{***}	0.014^{*}	-0.010	0.017^{***}	0.058^{***}	0.028^{**}	0.024^{*}	0.034^{**}	0.031^{**}	0.022^{*}
	(2.980)	(2.222)	(1.616)	(2.697)	(4.992)	(3.237)	(1.912)	(-0.824)	(2.360)	(6.642)	(2.061)	(1.756)	(2.182)	(2.180)	(1.804)
F p-Value	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
R^2 Within	20.4%	21.1%	19.3%	25.0%	20.2%	10.2%	10.1%	16.8%	8.6%	10.1%	30.9%	30.5%	36.2%	32.6%	24.1%

Newey and West (1987) heteroskedasticity and autocorrelation consistent t-statistics in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table presents equation 16 random effects panel regression results over forward 36-month horizons for value factors grouped by size. December 1972 to December 2022.

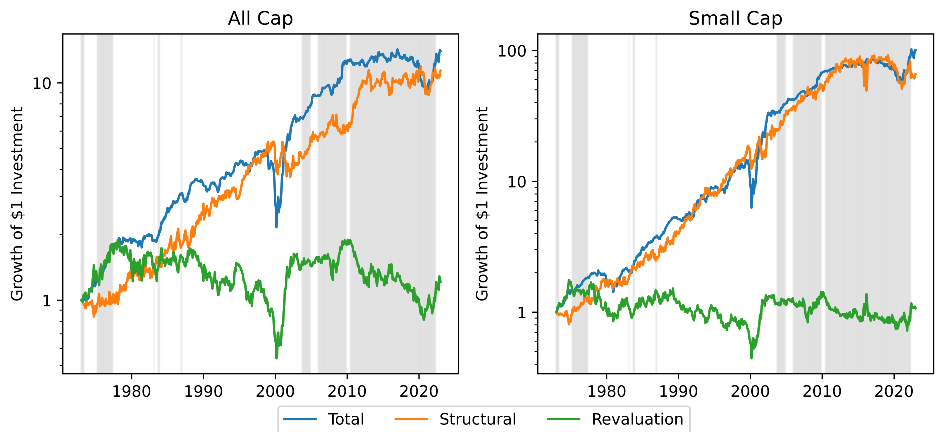
Table 10: Equation 16 Random Effects Panel Regression Results on All Decomposed Value Factor Forward 36-Month Returns by Signal Group

	Total Returns					Structural Returns					Revaluation Returns				
	Balance Sheet	Enterprise Value	Earnings	Cash Flow	Yield	Balance Sheet	Enterprise Value	Earnings	Cash Flow	Yield	Balance Sheet	Enterprise Value	Earnings	Cash Flow	Yield
α	−0.108*	−0.089*	−0.098**	−0.045*	−0.093***	0.093***	0.158***	0.131***	0.111***	0.097***	−0.111***	−0.180***	−0.217***	−0.104***	−0.160***
	(−1.839)	(−1.793)	(−2.137)	(−1.775)	(−2.901)	(2.662)	(3.755)	(2.763)	(2.680)	(3.740)	(−10.322)	(−11.489)	(−11.358)	(−5.500)	(−12.340)
$Value\ Spread_t$	0.035***	0.054***	0.061***	0.036***	0.065***	−0.010***	−0.053***	−0.061***	−0.058***	−0.055***	0.024***	0.078***	0.120***	0.064***	0.103***
	(12.377)	(4.131)	(9.230)	(2.542)	(9.962)	(−3.211)	(−4.560)	(−5.993)	(−4.810)	(−8.006)	(14.920)	(12.357)	(22.131)	(7.571)	(14.736)
$(F_LM_T)_t$	0.034***	0.078***	0.089***	0.058***	0.000	−0.010	0.025*	0.046**	0.030	0.010	0.032***	0.042***	0.041**	0.020	−0.010
	(2.961)	(4.606)	(4.390)	(5.098)	(0.591)	(−0.847)	(1.793)	(2.247)	(1.412)	(1.311)	(3.297)	(2.821)	(2.075)	(0.867)	(−0.512)
$(F_TM_L)_t$	0.020	0.055***	0.043***	0.04***	−0.020	0.000	0.028**	0.040	0.020	−0.020	0.010	0.020	0.010	0.010	0.000
	(1.126)	(3.728)	(3.213)	(4.314)	(−1.498)	(0.039)	(2.261)	(1.623)	(1.488)	(−1.434)	(1.002)	(1.628)	(0.774)	(0.783)	(−0.092)
$(F_TM_T)_t$	0.030**	0.055***	0.046***	0.063***	−0.010	0.027***	0.033***	0.000	0.073***	0.010	0.010	0.030	0.049***	−0.010	−0.010
	(2.095)	(3.058)	(2.664)	(4.346)	(−1.079)	(3.241)	(3.338)	(0.128)	(5.676)	(0.821)	(0.686)	(1.645)	(2.723)	(−0.781)	(−0.715)
F p-Value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
R^2 Within	23.2%	21.8%	26.2%	15.0%	22.9%	5.5%	17.9%	18.5%	22.0%	12.4%	28.9%	39.9%	46.6%	21.9%	37.6%

Newey and West (1987) heteroskedasticity and autocorrelation consistent t-statistics in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table presents equation 16 random effects panel regression results over forward 36-month horizons for value factors grouped by signal group as documented in table 1. December 1972 to December 2022.

Figure 6: Median Decomposed Returns to Enterprise Value Factors by Size



This figure plots the median cumulative return of a \$1 investment in the decomposition of the enterprise value factors by taking a new percentile every month of all underlying factors. The grey shaded regions indicate those periods when fiscal and monetary policy are jointly loose, $F_L M_L$*. December 1972 to December 2022.*

is for the enterprise value factors, while for others it is the combination of both structural and revaluation returns, neither of which are necessarily large (or significant) across regimes, that drives differences in total returns.

Given that the enterprise value and small cap factors seem to exhibit the strongest response to joint regimes of fiscal and monetary policy with respect to forward 36-month decomposed performance, I plot the intersection of their median total, structural, and revaluation returns over time in figure 6 compared with the all cap enterprise value factors. I show the $F_L M_L$ joint policy regime periods in grey to highlight the nature of the returns during such periods, in particular during the 2010s period.

I emphasize specifically the period starting with QE3, which began in September 2012, to the end of the jointly loose fiscal and monetary policy regimes in April 2022. This specific period coincides with among the loosest joint policies ever experienced in the post-Bretton Woods era, as shown by figures 2 and 3, and was signalled to be one in which policymakers were committed to raising the level of inflation with loose policy[18]. Since it is nearly a decade long, it is a perfect candidate period to examine more closely for the set of factors that I found previously to respond most to policy regimes. Furthermore, over this time period, the HML factor of Fama and French (1993) experienced an annualized total return of -1.4%, making it an important period to assess with respect to determining why value's performance was so abysmal. I take as my return series the median returns from figure 6.

From September 2012 to April 2022, the median enterprise value factor's total cumulative return implied an annualized return of 0.3%, composed of a 1.1% structural return and a -0.4% revaluation

[18] Board of Governors of the Federal Reserve System: Press Release October 24th, 2012. `https://www.federalreserve.gov/newsevents/pressreleases/monetary20121024a.htm`

return[19]. It would appear from this result that even during one of the loosest joint policy regimes in history, the structural return to enterprise value factors was still positive, implying that without any changes in the levels of relative valuations, an investor in such factors would still have made a positive return. However, this aggregate result masks the damage done to the cross-sectional value premium under the surface. For the small cap enterprise value factors, the median total return over this time period was 2.7% annualized, composed of a -2.1% structural return and a 1.6% revaluation return. An investor in such factors would therefore have, without the small benefit from revaluation, actually realized a negative total return over a nearly decade-long period.

Compared with the 50-year full sample, these returns are very abnormal. Over the long-run, the median enterprise value factor's total return was 5.7%, composed of structural and revaluation returns of 5.5% and 0.3%, respectively, while the small cap enterprise value factors experienced median annualized total, structural, and revaluation returns of 9.7%, 8.7%, and 0.1%, respectively. The implication of these results is admittedly somewhat troubling for value; while papers such as Israel, Laursen, and Richardson (2021) and Bellone and de Carvalho (2022) have suggested that value's recent performance is primarily due to relative valuation changes, my results, obtained by examining value's performance through the lens of joint fiscal and monetary policy regimes, suggest that extremely loose policies are not just damaging to revaluation returns, but to structural returns as well. Indeed, the explanatory results of tables 6 and 7 specifically show that average total value factor premiums, composed of both structural and revaluation returns, during jointly loose fiscal and monetary policy regimes are zero across design choices and in aggregate. Of course, this conclusion depends on the type of value factor examined. Here, I dove more deeply into the enterprise value factors, a popular formulation used by papers such as Asness, Friedman, Krail, and Liew (2000), which seem to respond the most to joint policy regimes across the methodologies I have employed. Nonetheless, my hypothesis that fiscal and monetary policy primarily act through the revaluation channel appears to be only partially confirmed by the results of tables 8, 9, and 10, as well as figure 6.

5 Factor Timing

5.1 Timing Methodology

Based on the results from Section 4, I conclude that fiscal and monetary policy regimes have a material impact on the forward medium-term returns to the concept of the cross-sectional value premium. Given that finding, I turn to the task of using the information contained in fiscal and monetary policy to create various timing strategies across my custom suite of 768 value factors.

[19] Note: return decomposition does not hold exactly as the results are aggregated across enterprise value factors. If one specific factor were examined, the decomposition is a mathematical identity.

For my investigation, I take the perspective of a long-term value factor investor. This investor's strategic portfolio is to hold the cross-sectional value portfolio. For example, if the investor's mandate is to invest in the traditional HML factor of Fama and French (1993), which in my custom suite is most closely modeled by the be_me, all cap, moderate, value-weighted, sector-agnostic factor, this investor would hold over the long-run that cross-sectional HML factor. However, given what Section 4 revealed, it is evident that the value factor goes through medium-run cycles that are at least in part driven by joint fiscal and monetary policy regimes. As such, the investor may desire to tactically adjust their exposure to value to conform with a policy-based prediction of forward returns at each point in time. For my timing strategies, I restrict the investor to only adjusting their exposure to value down (and not below zero), and do not allow for additional leverage beyond the 200% gross that is currently being employed across each monthly-rebalanced, long/short, zero-net factor. The reason is that the investor is strategically already fully invested in value, and desires to improve upon this strategy by tactically underweighting the factor if expected forward returns are low/negative. When expected returns are positive, which is generally the case for a well-known and robust cross-sectional premium such as value, the investor already has full exposure. If the investor would tactically reduce their exposure to value, they substitute this exposure with holding the risk-free asset, defined as the one month Treasury bill rate[20], such that gross and net leverage are always 200% and 0%, respectively. The task is therefore to assess whether information in fiscal and monetary policy can be used to avoid periods of low (or negative) value factor returns in favor of cash.

My approach to constructing a timing strategy is primarily based on the work of Czasonis, Kritzman, and Turkington (2023) and Czasonis, Kritzman, and Turkington (2020a). The authors formulate "CKT" regressions[21] that incorporate the concept of relevance, a measure derived from the Mahalanobis distance and similarly calculated to equation 8. I adopt their methodology and apply it to the policy variables noted in the Robustness Check discussion of Subsection 3.2. As a control variable for each individual value factor, I also include each factor's level of its $Value\ Spread$. On a quarterly basis, matching the slowest updating schedule for the policy variables, I apply CKT regressions to forecast forward 3-month (until the next quarterly update) value factor returns. I begin forecasting in December 1992, allowing for 20 training years of data with which to use. My CKT regressions are evaluated from there on an expanding basis using only information that would have been available to an investor at each point in time with no look-ahead bias, thereby representing fully out-of-sample predictions; as such, I do not make use of the results from Section 4, which are full sample regressions. For the training data, I therefore only examine up to three months prior to each point in time, as forward 3-month returns would clearly not be available after that. So, for the

[20] Ken French: Description of Fama/French Factors. `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html`

[21] For more information on implementation in Python, please see: `https://pypi.org/project/predictionrevisited/`

December 1992 start date, I only examine data up to September 1992 for training.

I begin by calculating the relevance, r_{it}, of each vector of prior observations of the independent variables, x_i, to the current set of circumstances, x_t. Relevance is defined in equation 17, composed of both similarity, in equation 18, and informativeness, in equation 19, where Ω^{-1} is the inverse of the nearest positive (semi-) definite covariance matrix of the independent variables up to the end of the training data.

$$r_{it} = sim(x_i, x_t) + \frac{1}{2}(info(x_i, \bar{x}) + info(x_t, \bar{x})) \tag{17}$$

$$sim(x_i, x_t) = -\frac{1}{2}(x_i - x_t)\Omega^{-1}(x_i - x_t)' \tag{18}$$

$$info(x_i, \bar{x}) = (x_i - \bar{x})\Omega^{-1}(x_i - \bar{x})' \tag{19}$$

Relevance implies that prior periods that are like the current observations but different from the historical average are more relevant to the current prediction task than those that are not. The task from here is to use the concept of relevance to form theoretically justified and appropriately weighted partial sample regressions that only select those prior observations that are most relevant to the current set of circumstances. As Czasonis, Kritzman, and Turkington (2023) demonstrate, the sum of the partial sample regression ("psr") weights is always one, as equation 20 shows.

$$w_{it,psr} = \frac{1}{N} + \frac{\lambda^2}{n-1}(\delta(r_{it})r_{it} - \varphi\bar{r}_{sub}) \tag{20}$$

In equation 20, $\delta(r_{it})$ is a censoring function that equals one if $r_{it} \geq r^*$, while n is the number of observations for which $\delta(r_{it}) = 1$ and $\varphi = \frac{n}{N}$ is the proportion of uncensored observations. Czasonis, Kritzman, and Turkington (2023) recommend that the relevance threshold in percentile terms across observations, r^*, is chosen in an iterative fashion from 0 to 0.9 such that the fit of the model, or the confidence in each individual prediction task, is maximized in the trade-off between decreasing the number of observations in the partial sample regression while increasing sub-sample fit among the uncensored observations. As fit is directly proportional to the regression's R^2, as shown in equation 21, increasing fit for each specific prediction task is equivalent to raising the explanatory power of the model, a desirable characteristic.

$$R^2 = \frac{1}{T-1}\sum_t info(x_t)fit_t \tag{21}$$

I proceed to calculate forward 3-month predictive CKT regressions on a quarterly basis in this fashion from December 1992 to December 2022. This results in a time series of such predictions over the 30-year out-of-sample period for each factor. I examine all 768 factors, regardless of whether they were efficacious in the training period, as strategic portfolios for 768 hypothetical different investors. I leave for future research the possibility of narrowing the scope of the factors to a subset that, in the training period, have statistically significantly positive Sharpe ratios or performance more broadly defined. This methodology would simulate what an actual investor might invest in beginning in December 1992, after controlling for multiple hypothesis testing using the procedures laid out in Kessler, Scherer, and Harries (2020), which were motivated by both White (2000) and Harvey and Liu (2015).

From here, I test several methodologies to transform CKT regression predictions into weights, all with an eye toward parsimony and simplicity to avoid overfitting with the benefit of hindsight. Clearly, more complex timing strategies could be developed with respect to weighting decisions or the inclusion of other variables known to be impactful, as discussed by Ilmanen, Israel, Lee, Moskowitz, and Thapar (2021), among others. However, since the primary purpose of my paper is to evaluate the value factor in the context of joint fiscal and monetary policy regimes, I limit my search to a small set of weighting schemes among the policy variables that I have selected for examination. I leave further development of value factor timing strategies for future research.

The first timing approach I examine, "Fit", derives the tactical value factor weight, $w_{i,value}$, from equation 22; the weight applied to the risk-free rate, $w_{i,rf}$, is simply given by $1 - w_{i,value}$. Note that $w_{i,value}$ will always fall between zero and one, implying that any positive factor performance predictions simply lead to the investor's strategic allocation to cross-sectional value of 100% of notional exposure. I examine the sign of the forward 3-month return prediction, $\hat{r}_{i,t,t+3}$, and multiply this value by the fit, $Fit_{i,t}$[22], of that specific prediction task, indicative of the confidence the investor would have in their forecast.

$$w^{Fit}_{i,value} = max(min(1 + sgn(\hat{r}_{i,t,t+3}) \times Fit_{i,t}, 1), 0) \tag{22}$$

I also consider a approach similar to equation 22, but in this one, "FitPred", I also include the value of the prediction itself. The intuition is that, in conjunction with confidence as measured by $Fit_{i,t}$, predictions for $\hat{r}_{i,t,t+3}$ that are more negative are more bearish in magnitude on the forward 3-month prospect of value than those that are less negative, and therefore are deserving of a greater tactical tilt. Equation 23 illustrates this approach.

[22] Since the average and 95th percentile values of fit over the entire out-of-sample period across all 768 factors are 1.6% and 5.4%, respectively, I arbitrarily multiply the value of $Fit_{i,t}$ by 10 to maximize the size of the tactical bet taken. This provides greater dispersion between the strategic and tactical results for the purpose of examining whether a timing strategy is efficacious. Asness, Chandra, Ilmanen, and Israel (2017) show that value timing based on relative valuation spreads is most clearly differentiated from a strategic position when the relative bet sizes are in magnitude larger than 50%, which corresponds to the broad range of the values of $Fit_{i,t}$ I find from the CKT regressions. I apply this multiplying factor throughout equations 22, 23, 24, and 25, including to predicted returns given that they are of similarly small magnitude to $Fit_{i,t}$ across all factors.

$$w_{i,value}^{FitPred} = max(min(1 + sgn(\hat{r}_{i,t,t+3}) \times Fit_{i,t} + \hat{r}_{i,t,t+3}, 1), 0) \tag{23}$$

From tables 8, 9, and 10, it is clear that forward value factor returns are also at least in part explained by the current joint policy regime. Given this, I similarly employ a regime-based timing strategy interacted with equations 22, "FitRegime", and 23, "FitPredRegime". Specifically, I first calculate, on an expanding basis with no look-ahead bias, the average forward 3-month returns to each value factor over the full sample and in each joint policy regime up to the end of the training data (i.e., September 1992 for the first prediction). Then, I take the difference of each regime's average forward returns to date and the full sample average, and use this measure, $\hat{r}_{d,i,t,t+3}$, as the tactical value factor weight adjustment that the investor would use[23]. The FitRegime and FitPredRegime weighting schemes are shown in equations 24 and 25, respectively.

$$w_{i,value}^{FitRegime} = max(min(1 + sgn(\hat{r}_{i,t,t+3}) \times Fit_{i,t} + \hat{r}_{d,i,t,t+3}, 1), 0) \tag{24}$$

$$w_{i,value}^{FitPredRegime} = max(min(1 + sgn(\hat{r}_{i,t,t+3}) \times Fit_{i,t} + \hat{r}_{i,t,t+3} + \hat{r}_{d,i,t,t+3}, 1), 0) \tag{25}$$

I then evaluate each timing strategy along multiple dimensions over the 30-year out-of-sample period from December 1992 to December 2022. Though I use a mosaic approach, I also specifically test the efficacy of each timing strategy relative to the corresponding strategic portfolio on a Sharpe ratio basis using the work of Lo (2002), Riondato (2018), and Christie (2005). In order to test the difference between two Sharpe ratios, I apply a generalized method of moments ("GMM") procedure to obtain $\hat{\theta}_i = (\hat{\mu}_{i,Ta}, \hat{\sigma}_{i,Ta}, \hat{\mu}_{i,St}, \hat{\sigma}_{i,St})$ and $\hat{\Omega}_i = \frac{1}{T}(\hat{d}_i{}' \hat{S}_i{}^{-1} \hat{d}_i)^{-1}$, where $\hat{\theta}_i$ is the parameter vector, $\hat{\mu}_{i,St}$ and $\hat{\sigma}_{i,St}$ are the mean and standard deviation, respectively, of strategic portfolio i, Ta refers to a particular tactical timing strategy for factor i, and $\hat{\Omega}_i$ is the asymptotic variance of $\hat{\theta}_i$. With null and alternative hypotheses $H_0 : \frac{\mu_{i,Ta}}{\sigma_{i,Ta}} - \frac{\mu_{i,St}}{\sigma_{i,St}} = 0$ and $H_a : \frac{\mu_{i,Ta}}{\sigma_{i,Ta}} - \frac{\mu_{i,St}}{\sigma_{i,St}} \neq 0$, respectively, I derive the following estimates for $\hat{d}_i$ and $\hat{S}_i$:

$$\hat{d}_i = \frac{\partial \hat{E}[f(x_t^i, \hat{\theta}_i)]}{\partial \hat{\theta}_i'} = \begin{pmatrix} -1 & 0 & 0 & 0 \\ 0 & -2\hat{\sigma}_{i,Ta} & 0 & 0 \\ 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & -2\hat{\sigma}_{i,St} \end{pmatrix} \tag{26}$$

[23]Note: the results are materially similar when using the medium-term forward 36-month returns to value, following tables 8, 9, and 10.

$$\hat{S}_i = \hat{E}[f(x_t^i,\hat{\theta}_i)f(x_t^i,\hat{\theta}_i)'] = \hat{E}\Bigg[\begin{pmatrix} x_t^{i,Ta} - \hat{\mu}_{i,Ta} \\ (x_t^{i,Ta} - \hat{\mu}_{i,Ta})^2 - \hat{\sigma}^2_{i,Ta} \\ x_t^{i,St} - \hat{\mu}_{i,St} \\ (x_t^{i,St} - \hat{\mu}_{i,St})^2 - \hat{\sigma}^2_{i,St} \end{pmatrix}\begin{pmatrix} x_t^{i,Ta} - \hat{\mu}_{i,Ta} \\ (x_t^{i,Ta} - \hat{\mu}_{i,Ta})^2 - \hat{\sigma}^2_{i,Ta} \\ x_t^{i,St} - \hat{\mu}_{i,St} \\ (x_t^{i,St} - \hat{\mu}_{i,St})^2 - \hat{\sigma}^2_{i,St} \end{pmatrix}'\Bigg] \tag{27}$$

Using equations 26 and 27, I then construct a test statistic, ξ_i, as follows:

$$\xi_i = h(\hat{\theta}_i)'\hat{V_i}^{-1}h(\hat{\theta}_i) \sim \chi^2(dim\ h(\hat{\theta}_i)) \tag{28}$$

In equation 28, $h(\hat{\theta}_i) = \frac{\hat{\mu}_{i,Ta}}{\hat{\sigma}_{i,Ta}} - \frac{\hat{\mu}_{i,St}}{\hat{\sigma}_{i,St}}$, and $\hat{V_i}$ is given by equation 29:

$$\hat{V_i} = \hat{A}_i\hat{\Omega}_i\hat{A}_i' \tag{29}$$

In equation 29, $\hat{A}_i = \frac{\partial h(\hat{\theta}_i)}{\partial \hat{\theta}_i'} = \begin{bmatrix} \frac{1}{\hat{\sigma}_{i,Ta}} & -\frac{\hat{\mu}_{i,Ta}}{(\hat{\sigma}_{i,Ta})^2} & -\frac{1}{\hat{\sigma}_{i,St}} & \frac{\hat{\mu}_{i,St}}{(\hat{\sigma}_{i,St})^2} \end{bmatrix}$. I apply this GMM-based Sharpe ratio comparison test to each timing strategy relative to their corresponding strategic portfolio across all 768 value factors.

5.2 Note on Multiple Hypothesis Testing

Since I am testing 768 value factors across each of the four timing methodologies discussed in the previous section, a major issue to account for is that of multiple hypothesis testing. I manage this problem by using the Bonferroni correction, appropriately adjusted for the fact that I am using correlated dependent variables. Nyholt (2004) suggests an equation to identify the effective number of tests, M_{eff}, among M correlated variables with a vector λ of eigenvalues of length M:

$$M_{eff} = 1 + (M-1) \times (1 - \frac{Var(\lambda)}{M}) \tag{30}$$

From here, M_{eff} in equation 30 is used to identify the Bonferroni-corrected α level in the presence of correlated tests, given by:

$$\alpha_{M_{eff}} = \frac{\alpha}{M_{eff}} \tag{31}$$

Examining the full sample data, I find the effective number of tests, M_{eff}, of the value factors to be 486, rounded up to the nearest whole number. I note that this estimate is likely conservative, as Kessler, Scherer, and Harries (2020), as well as my own factors, indicate that some value definitions capture the premium effectively while others generally lead to flat or negative annualized returns over the long-run, such as the yield factors. In other words, the wide span of value factors that I test artificially raises the number of tests I run, despite potentially not serving as effective unconditional factors. I leave this for future research though, in which I intend to explore only those factors whose Sharpe ratios or performance more broadly are statistically significantly positive in the training data, accounting for the issue of multiple hypothesis testing and the correlations between strategies. Regardless, this M_{eff} value of 486, multiplied by four to account for the four different timing strategies that I employ, leads to an $\alpha_{M_{eff}}$ value of 0.0026% to assess timing strategies that are statistically significantly better than the corresponding strategic portfolio on a Sharpe ratio basis.

5.3 Timing Results

To illustrate the unique CKT approach, I first plot an example of how the final regression as of December 2022 weighted each prior observation with respect to the independent variables' relevance to the current circumstances. I use the example of the *mbe_me* factor applied on the all cap, moderate, value-weighted, sector-agnostic portfolio construction design choices, the closest factor I have to the original Fama and French (1993) HML factor that nonetheless adjusts for intangible capital following Peters and Taylor (2017)[24]. Given broad familiarity with the HML factor and the importance of estimates of intangible capital, I choose to focus specifically on this factor and the classic HML one throughout this section for certain results. Figure 7 depicts the relevance of each prior period to December 2022's forward 3-month prediction, with the current joint fiscal and monetary policy regime, $F_T M_T$, highlighted in grey.

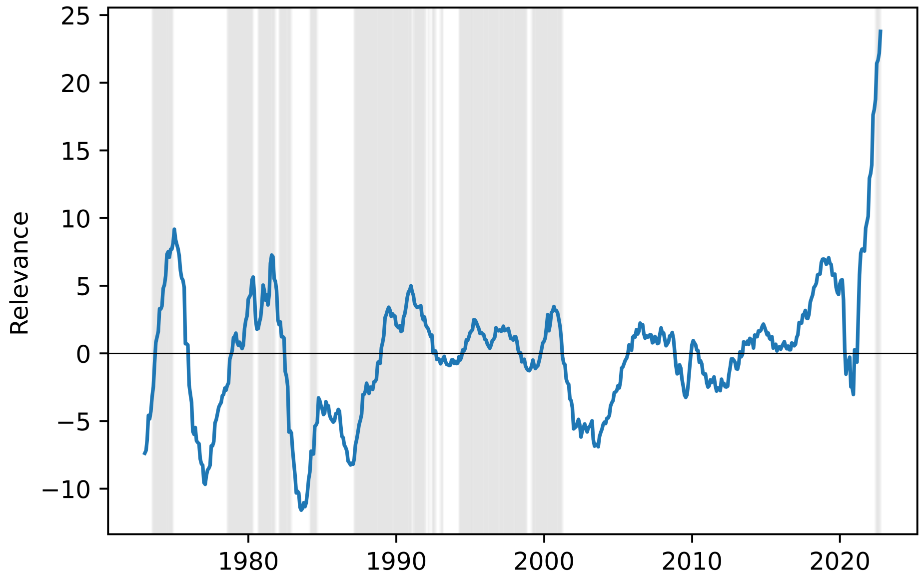
The more recent observations are of course more relevant to the current prediction task, but further back in history, the most relevant observations are generally those that correspond to other periods of jointly tight fiscal and monetary policy. Figure 7 highlights two key results: 1) the CKT regressions are highly flexible and suited to time-varying predictions, as each forecast from December 1992 to December 2022 has a different view of relevance with respect to all prior observations on an expanding basis; and 2) joint fiscal and monetary policy regimes are highly important to selecting weights for the partial sample regressions, even in a completely empirical setting. No binary variables for each regime were included as relevance was determined solely using equations 17 and the censoring function of equation 20, all with fully point-in-time data.

To evaluate each timing strategy discussed in the Timing Methodology subsection, I begin by simply calculating the out-of-sample correlations between the predicted returns from the CKT regressions, $\hat{r}_{i,t,t+3}$, and regime-based approach, $\hat{r}_{i,t,t+3} + \hat{r}_{d,i,t,t+3}$, with realized 3-month returns to each value factor. Table 11 shows these correlations at the aggregate level across all factors, as well as segmented by signal group and size.

Table 11 indicates that the most relevant observations, or those selected with $r_{it} \geq r^*$ from equation 20, in all cases have higher out-of-sample prediction correlations to ultimate realized 3-month returns than the least relevant observations, highlighting the unique approach of the CKT regres-

[24]Note: figure 7 is materially the same using the *be_me* factor with the same portfolio construction design choices.

Figure 7: Relevance of Prior Observations Relative to December 2022 Forecast for HML-Style *mbe_me* Factor



This figure plots the relevance of each prior observation of the independent policy variables and control relative valuation spread for the mbe_me, all cap, moderate, value-weighted, sector-agnostic value factor as of the final December 2022 prediction. The grey shaded regions correspond to the current joint fiscal and monetary policy regime, $F_T M_T$. December 1972 to December 2022.

Table 11: Correlations between Predicted and Realized Forward 3-Month Returns for CKT Regressions and Regime-Based Approach by Relevance Category

			Size				Signal Group				
Prediction	Relevance Category	All Factors	All	Mega	Large	Small	Balance Sheet	Enterprise Value	Earnings	Cash Flow	Yield
$\hat{r}_{i,t,t+3}$	Most	10.1%	7.4%	4.1%	9.2%	14.0%	20.5%	7.9%	7.6%	0.2%	3.3%
$\hat{r}_{i,t,t+3}$	Least	2.8%	1.7%	-5.4%	-2.2%	10.4%	6.8%	1.7%	-1.2%	2.2%	0.5%
$\hat{r}_{i,t,t+3} + \hat{r}_{d,i,t,t+3}$	Most	8.7%	6.3%	3.3%	7.8%	12.8%	18.9%	6.7%	6.5%	0.0%	2.0%
$\hat{r}_{i,t,t+3} + \hat{r}_{d,i,t,t+3}$	Least	1.7%	0.8%	-5.5%	-3.0%	9.5%	5.2%	0.7%	-1.8%	1.8%	-0.8%

This table presents the correlation between forward 3-month return predictions and ultimate realized 3-month returns across all factors, as well as by size and signal group as documented in table 1. Predictions are segmented by most and least relevant observations from the CKT regressions following equation 20. December 1992 to December 2022.

Table 12: Median Performance Characteristics of Strategic and Tactically-Timed Value Factor Portfolios by Signal Group and Sector

Design Choice	Category	Strategy	Ann. Ret.	Ann. Vol.	Sharpe	Skew	Kurt.	95% VaR	95% CVaR	99% VaR	99% CVaR	MDD	MDD-to-Vol.
	All Factors	Strategic	3.0%	13.8%	0.25	0.18	6.87	4.7%	7.9%	9.6%	15.0%	52.2%	3.82
	All Factors	Fit	2.9%	11.7%	0.28	0.20	6.19	4.2%	7.0%	8.2%	12.5%	47.6%	3.95
	All Factors	FitPred	3.0%	10.7%	0.30	0.31	6.99	3.8%	6.4%	7.4%	11.1%	42.9%	3.88
	All Factors	FitRegime	3.0%	11.4%	0.29	0.24	6.14	4.1%	6.8%	8.0%	12.1%	46.3%	3.94
	All Factors	FitPredRegime	3.1%	10.6%	0.31	0.33	6.92	3.7%	6.4%	7.3%	10.8%	41.9%	3.86
Signal Group	Balance Sheet	Strategic	4.4%	13.3%	0.33	0.26	6.84	4.7%	7.5%	8.9%	12.8%	47.0%	3.49
Signal Group	Balance Sheet	Fit	4.1%	12.1%	0.34	0.26	6.58	4.4%	7.0%	8.2%	12.0%	44.7%	3.50
Signal Group	Balance Sheet	FitPred	4.1%	11.5%	0.37	0.25	6.49	4.3%	6.7%	8.0%	11.2%	43.7%	3.60
Signal Group	Balance Sheet	FitRegime	4.0%	12.0%	0.34	0.25	6.26	4.3%	6.9%	8.1%	11.6%	44.2%	3.59
Signal Group	Balance Sheet	FitPredRegime	4.1%	11.4%	0.37	0.24	6.49	4.3%	6.6%	8.0%	11.0%	43.5%	3.63
Signal Group	Enterprise Value	Strategic	5.0%	14.8%	0.39	0.12	7.91	4.7%	8.6%	9.7%	16.8%	54.8%	3.72
Signal Group	Enterprise Value	Fit	4.6%	12.5%	0.42	0.13	6.95	4.1%	7.3%	8.3%	13.7%	51.5%	3.96
Signal Group	Enterprise Value	FitPred	4.7%	11.3%	0.43	0.32	7.33	3.8%	6.6%	7.7%	12.2%	44.8%	3.95
Signal Group	Enterprise Value	FitRegime	4.8%	12.3%	0.43	0.19	6.62	4.1%	7.1%	8.2%	13.4%	49.9%	3.97
Signal Group	Enterprise Value	FitPredRegime	4.7%	11.2%	0.44	0.39	7.53	3.7%	6.5%	7.5%	11.8%	43.0%	3.89
Signal Group	Earnings	Strategic	1.9%	15.3%	0.15	0.14	6.94	5.2%	9.3%	11.8%	16.7%	56.8%	3.88
Signal Group	Earnings	Fit	2.1%	12.5%	0.20	0.28	6.53	4.6%	7.4%	8.7%	13.0%	50.7%	4.13
Signal Group	Earnings	FitPred	2.3%	11.0%	0.23	0.41	8.49	3.9%	6.7%	7.8%	11.5%	44.0%	4.03
Signal Group	Earnings	FitRegime	2.2%	12.1%	0.22	0.35	6.56	4.4%	7.1%	8.3%	12.4%	48.3%	4.09
Signal Group	Earnings	FitPredRegime	2.5%	10.8%	0.24	0.46	8.66	3.8%	6.6%	7.7%	11.3%	42.5%	3.95
Signal Group	Cash Flow	Strategic	3.9%	13.4%	0.31	0.22	6.54	4.5%	7.6%	9.3%	14.6%	49.6%	3.64
Signal Group	Cash Flow	Fit	3.4%	11.5%	0.30	0.21	5.81	4.1%	7.0%	8.4%	12.2%	45.3%	3.92
Signal Group	Cash Flow	FitPred	3.3%	10.6%	0.33	0.30	6.21	3.9%	6.5%	7.4%	10.9%	42.3%	3.71
Signal Group	Cash Flow	FitRegime	3.3%	11.1%	0.31	0.26	5.73	4.0%	6.8%	8.2%	11.5%	44.4%	3.89
Signal Group	Cash Flow	FitPredRegime	3.3%	10.3%	0.33	0.29	6.37	3.7%	6.4%	7.3%	10.8%	41.8%	3.77
Signal Group	Yield	Strategic	0.8%	10.8%	0.09	0.16	5.99	3.9%	6.6%	7.8%	10.9%	43.2%	4.12
Signal Group	Yield	Fit	1.0%	9.4%	0.12	0.17	5.02	3.7%	5.6%	6.4%	9.7%	38.8%	4.13
Signal Group	Yield	FitPred	1.0%	8.5%	0.14	0.21	5.30	3.4%	5.1%	6.1%	8.3%	35.7%	4.09
Signal Group	Yield	FitRegime	1.1%	9.2%	0.14	0.19	5.14	3.6%	5.5%	6.3%	9.6%	37.8%	4.12
Signal Group	Yield	FitPredRegime	1.1%	8.5%	0.16	0.25	5.22	3.3%	5.0%	5.9%	8.3%	35.2%	4.12
Sector	SA	Strategic	3.3%	15.1%	0.23	0.02	7.12	5.2%	9.0%	10.8%	17.3%	57.2%	3.80
Sector	SA	Fit	3.0%	13.3%	0.25	0.09	6.60	4.8%	8.0%	9.5%	15.2%	54.5%	3.96
Sector	SA	FitPred	2.9%	11.9%	0.26	0.14	7.65	4.3%	7.2%	8.6%	13.5%	50.1%	3.99
Sector	SA	FitRegime	3.1%	12.9%	0.26	0.11	6.44	4.6%	7.7%	9.1%	14.6%	53.0%	3.94
Sector	SA	FitPredRegime	3.0%	11.8%	0.27	0.18	7.66	4.3%	7.1%	8.4%	13.2%	49.0%	3.96
Sector	SN	Strategic	3.0%	12.3%	0.27	0.35	6.57	4.2%	7.1%	8.6%	12.9%	46.8%	3.83
Sector	SN	Fit	2.8%	10.3%	0.31	0.42	5.62	3.6%	5.8%	7.0%	10.1%	39.3%	3.93
Sector	SN	FitPred	3.1%	9.4%	0.35	0.51	6.24	3.4%	5.4%	6.4%	9.3%	34.6%	3.76
Sector	SN	FitRegime	2.9%	10.1%	0.32	0.45	5.66	3.6%	5.7%	6.8%	9.7%	37.9%	3.88
Sector	SN	FitPredRegime	3.1%	9.4%	0.36	0.54	6.28	3.3%	5.4%	6.3%	9.2%	33.9%	3.69

This table presents the median performance summary statistics for both strategic and tactically-timed value factor portfolios across all factors, as well as by signal group as documented in table 1 and sector. Tactical strategies are formed using the approaches documented in the Timing Methodology subsection, and specifically equations 22, 23, 24, and 25. Ann. Ret. is annualized return, Ann. Vol. is annualized volatility, Sharpe is the Sharpe ratio, Skew is skewness, Kurt. is excess kurtosis, VaR is value-at-risk, CVaR is conditional-value-at-risk, MDD is max drawdown, and MDD-to-Vol. is max drawdown-to-annualized volatility. December 1992 to December 2022.

sions. The only exceptions are the cash flow factors, which do not appear to have any predictability at all using the information contained in fiscal and monetary policy. Across all factors, the CKT regression predictions are 10.1% correlated with realized returns, with the strongest predictive ability in the small cap and balance sheet factors.

From here, I examine whether the timing strategies, as documented in equations 22, 23, 24, and 25, in aggregate improve on the long-run performance and characteristics of each strategic investor's portfolio across the 768 factors. Table 12 presents the median outcome for each strategic portfolio and timing strategy across all factors and by signal group and sub-portfolio sector scheme.

Relative to the strategic portfolios, the tactical timing strategies all generally lead to a small increase in Sharpe ratio, primarily attributable to lower volatility, as well as an increase in skewness and decreases in excess kurtosis, VaR/CVaR measures, and max drawdown. However, the cost of the slightly improved Sharpe ratio across all factors is also generally a small increase in the MDD metric. Across all factors, the most effective signals appear to be FitPred and FitPredRegime, which maintain the same level of returns at the 50th percentile while meaningfully reducing volatility and risk metrics such as VaR, CVaR, and max drawdown. The median Sharpe ratio for these two tactical timing approaches improves upon the median strategic portfolio's Sharpe ratio by 22.4% and 25.2%, respectively. The strongest results appear to be concentrated within the earnings and sector-neutral factors, at least at the median of those two design choice categories. With respect to timing strategies, the FitPred and FitPredRegime approaches appear to be most promising across all factors and within the select category choices that I show in table 12. These incorporate not only the $Fit_{i,t}$ of each CKT regression, but additionally the magnitude of the return forecasts from the CKT regressions and the regime-based methodology, respectively. I conclude that adding in these forecasts, even in a very simple way as shown in equations 23 and 25, leads to marginally improved performance across the summary statistics that I present.

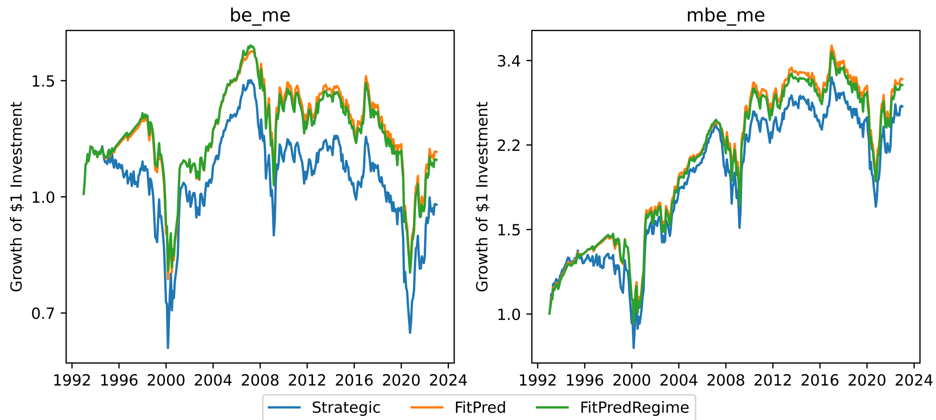
To complement the results in table 12, I examine each timing strategy's Sharpe ratio in comparison to the respective strategic portfolio for all 768 value factors using the GMM procedure detailed in the Timing Methodology subsection. Unfortunately, when I account for multiple hypothesis testing using the Nyholt (2004) Bonferroni-corrected $\alpha_{M_{eff}}$ value of 0.0026%, I find that none of the timing strategies I propose achieve a statistically significant increase in Sharpe ratio relative to the strategic portfolio. At the $\alpha = 5\%$ level, I reject H_0 in favor of H_a using equation 28 for 7.7% and 7.0%, respectively, of the FitPred and FitPredRegime timing methodologies across all 768 value factors, little more than would be expected by chance for such a large parameter space. My conclusion is therefore that using the information contained in fiscal and monetary policy, at least based on the simple and parsimonious approaches I have adopted to date, only weakly improves the performance of a strategically held cross-sectional value factor.

Despite that conclusion, to examine more closely the behavior of the time series of the tactical portfolios relative to the strategic portfolios, I select both the be_me and mbe_me factors that are closest to the well-known and original Fama and French (1993) specification in that they are formed using the all cap, moderate, value-weighted, sector-agnostic portfolio construction design choices[25]. Figure 8 presents the cumulative growth of a \$1 investment in each factor's strategic, FitPred, and FitPredRegime portfolios. The benefits, though small, of these timing strategies seem to stem primarily from the mid- to late-1990s period, as well as at times during the 2010s. This is perhaps not surprising, as those periods were among the worst on record since the 1920s for cross-sectional value, and the timing strategies I have employed are all aimed at reducing exposure tactically during periods when forward return forecasts are low.

From the results in this section, I conclude that value timing using parsimonious approaches only

[25]The correlation between the be_me, all cap, moderate, value-weighted, sector-agnostic factor and the HML factor of Fama and French (1993) over the full sample from December 1972 to December 2022 is 78.3%. This rises to 91.4% compared with the HML-Devil factor of Asness and Frazzini (2013), which uses a monthly-rebalancing policy, and to 94.3% compared with the closest version of Jensen, Kelly, and Pedersen (2021).

Figure 8: Strategic versus Tactical Portfolio Performance for HML-Style *be_me* and *mbe_me* Factors



This figure plots the growth of a \$1 investment in HML-style be_me and mbe_me, all cap, moderate, value-weighted, sector-agnostic value factors. The strategic portfolios are compared against the FitPred and FitPredRegime approaches of equations 23 and 25 for both portfolios. December 1992 to December 2022.

weakly improves on a strategic exposure to the factor. I leave for future research various additional improvements to the methodologies presented here, including, but not limited to: 1) narrowing the scope of the factors to a subset that, in the training period, have statistically significantly positive Sharpe ratios or performance more broadly, to simulate what an actual investor might have invested in with the information at their disposal as of December 1992; 2) expanding my search to additional countries for robustness checks; and 3) evaluating more sophisticated tactical weighting approaches beyond the purposefully simple ones employed here. Using these extensions, I intend to explore further whether there are indeed timing strategies that are efficacious for the cross-sectional value factor.

6 Conclusion

Time-varying returns to the cross-sectional value factor in the post-Bretton Woods era are at least in part explained by fiscal and monetary policy. This conclusion is consistent regardless of the specification of value with respect to five portfolio construction design choices: 1) signal; 2) size; 3) value; 4) weight; and 5) sector. Furthermore, it is robust to definitions of fiscal and monetary policy, including regime classification methodology.

In the short-run around FOMC meetings, there is weak evidence that value factors are negatively geared to changes in Fed Funds target rates, and no evidence that other policy-related variables such as the EPU index of Baker, Bloom, and Davis (2016) have any bearing on this relationship. Across signal groups, the balance sheet factors are in aggregate the ones that are most sensitive to both expected and unexpected changes in the Fed Funds target rate. The primary reason for this change appears to be the highly net levered nature of those factors as compared to other signal groups, making their nearer-term cash flows more exposed to monetary policy actions due to refinancing concerns. Indeed, the pre-announcement drift of the abnormal returns to the balance sheet factors prior to Fed Funds rate decreases, as opposed to the *div_me* factors, for example, suggests that the *be_me*, *mbe_me*, and *at_me* factors benefit in the short-run from expectations of looser monetary policy.

In the medium-run, the primary focus of this paper, the impact of fiscal and monetary policy joint regimes on the cross-sectional value factor is clear: tighter regimes lead to higher returns than looser regimes. My hypothesis was that it would be revaluation that primarily drove the time-variation in value factor returns with respect to joint policy regimes. However, my results ultimately suggest that it is both structural and revaluation returns that differ across regimes, with both components generally higher in tighter regimes than in looser regimes. This finding is consistent across all 768 factors in aggregate, including specifically for many of the portfolio construction design choice groupings individually. I take this conclusion to be somewhat troubling for the concept of the value premium during future periods of loose fiscal and monetary policy. To the extent that the time-variation was primarily due to revaluation returns across joint policy regimes, long-run value investors could still rely on positive structural returns to mitigate any losses due to revaluation, and also benefit in the future from the high expected returns associated with wider relative valuation spreads. Indeed, this was the story of the post-GFC period; although the HML factor of Fama and French (1993) generated annualized returns of -5.1% from June 2009 to September 2020, the period from October 2020, when the latest value factor rally begin in earnest, to December 2022 delivered investors a 26.2% annualized return. This return far outstripped that of the CRSP value-weighted index, which generated 5.2% over the same time period. That 26.2% return, furthermore, was in the 98.4th percentile of all rolling 26-month periods for the HML factor since July 1926, surpassed only by the returns to value following the Dot-Com bubble of the late 1990s/early 2000s, and was primarily driven by revaluation.

However, despite that nice narrative, a significant reason that value suffered in the post-GFC period was not just due to changes in relative valuations. Across nearly all factor definitions, structural returns were lower than the long-run average. More accurately, during periods of jointly loose fiscal and monetary policy, structural returns are statistically lower than in other policy regimes. I leave for future research the dissection of this component of value factor returns across policy regimes, though one promising avenue based on the results presented here is to examine differences in net leverage, efficiency, and other fundamental characteristics of the long/short factors.

Finally, using the information contained in fiscal and monetary policy appears to be only weakly useful in simple factor timing strategies on a fully out-of-sample basis with no look-ahead bias, matching the results of many other papers on this topic. Strategic investors in the cross-sectional value factor could benefit, albeit not in a statistically significant way on a Sharpe ratio basis when accounting for the issue of multiple hypothesis testing, from tactically reducing their exposure based on short-term forecasts of returns derived solely from policy variable information, controlling for the level of relative valuation spreads. As discussed in Subsection 5.3, I similarly leave to future research more nuanced and complex weighting approaches with additional variables across more countries, but the CKT regression methodology of Czasonis, Kritzman, and Turkington (2023) provides a promising lens through which to view the question of factor timing in the context of macroeconomic variables such as fiscal and monetary policy.

References

[1] Afonso, A. and Sousa, R. (2011). What are the effects of fiscal policy on asset markets? *Economic Modelling*, 28(4):1871–1890.

[2] Afonso, A. and Sousa, R. (2012). The macroeconomic effects of fiscal policy. *Applied Economics*, 44(34):4439–4454.

[3] Agnello, L. and Sousa, R. M. (2013). Fiscal policy and asset prices. *Bulletin of Economic Research*, 65(2):154–177.

[4] Anderson, T. W. (1962). On the distribution of the two-sample cramer-von mises criterion. *The Annals of Mathematical Statistics*, 33(3):1148–1159.

[5] Ang, A. (2023). Trends and cycles of style factors in the 20th and 21st centuries. *The Journal of Portfolio Management*, 49(4):33–56.

[6] AQR. Value: Why now? capturing the comeback in its early innings. AQR Fourth Quarter 2022.

[7] Ardagna, S. (2009). Financial markets' behavior around episodes of large changes in the fiscal stance. *European Economic Review*, 53(1):37–55.

[8] Arnott, R. D. and Ko, A. (2023). Revisting our "horribly wrong" paper: That was then, this is now. Research Affiliates.

[9] Arnott, R. D., Beck, N., and Kalesnik, V. (2016a). Timing "smart beta" strategies? of course! buy low, sell high! Research Affiliates.

[10] Arnott, R. D., Beck, N., and Kalesnik, V. (2016b). To win with "smart beta", ask if the price is right. Research Affiliates.

[11] Arnott, R. D., Beck, N., Kalesnik, V., and West, J. (2016). How can "smart beta" go horribly wrong? Research Affiliates.

[12] Arnott, R. D., Harvey, C. R., Kalesnik, V., and Linnainmaa, J. T. (2021). Report's of value's death may be greatly exaggerated. *Financial Analysts Journal*, 77(1):44–67.

[13] Asness, C. S. (2016a). The siren song of factor timing aka "smart beta timing" aka "style timing". *The Journal of Portfolio Management*, 42(5):1–6.

[14] Asness, C. S. (2016b). My factor philippic. AQR.

[15] Asness, C. S. (2021). The long run is lying to you. AQR: Cliff's Perspectives.

[16] Asness, C. S. and Frazzini, A. (2013). The devil in hml's details. *The Journal of Portfolio Management*, 39(4):49–68.

[17] Asness, C. S., Chandra, S., Ilmanen, A., and Israel, R. (2017). Contrarian factor timing is deceptively difficult. *The Journal of Portfolio Management*, 43(5):72–87.

[18] Asness, C. S., Frazzini, A., Israel, R., and Moskowitz, T. J. (2015). Fact, fiction, and value investing. *The Journal of Portfolio Management*, 42(1):34–52.

[19] Asness, C. S., Friedman, J. A., Krail, R. J., and Liew, J. M. (2000). Style timing: Value versus growth. *The Journal of Portfolio Management*, 26(3):50–60.

[20] Asness, C. S., Liew, J. M., Pedersen, L. H., and Thapar, A. (2021). Deep value. *The Journal of Portfolio Management*, 49(4).

[21] Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636.

[22] Ball, R., Gerakos, J., Linnainmaa, J. T., and Nikolaev, V. V. (2015). Deflating profitability. *Journal of Financial Economics*, 117(2):225–248.

[23] Banerjee, R. N., Boctor, V., Mehrotra, A., and Zampolli, F. (2022). Fiscal deficits and inflation risks: the role of fiscal and monetary policy regimes. BIS Working Paper No. 1028.

[24] Basu, S. (1983). The relationship between earnings' yield, market value and return for nyse common stocks: Further evidence. *Journal of Financial Economics*, 12(1):129–156.

[25] Baz, J., Davis, J., Beck-Friis, P., Tsai, J., and Zhang, Z. (2021). Assessing inflation: Theories, policies, and portfolios. PIMCO Research.

[26] Bellone, B. and de Carvalho, R. L. (2022). Value versus glamour stocks: The return of irrational exuberance? *The Journal of Investing*, 31(2):75–93.

[27] Belo, F., Gala, V. D., and Li, J. (2013). Government spending, political cycles, and the cross-section of stock returns. *Journal of Financial Economics*, 107(2):305–324.

[28] Bender, J., Sun, X., Thomas, R., and Zdorovtsov, V. (2018). The promises and pitfalls of factor timing. *The Journal of Portfolio Management*, 44(4):79–92.

[29] Bernanke, B. S. and Kuttner, K. N. (2005). What explains the stock market's reaction to federal reserve policy? *Journal of Finance*, 60(3):1221–1257.

[30] Bianchi, F. (2012). Evolving monetary/fiscal policy mix in the united states. *American Economic Review*, 102(3):167–72.

[31] Blanchard, O. (1990). Suggestions for a new set of fiscal indicators. OECD Economics Department Working Paper No. 79.

[32] Blitz, D. and Hanauer, M. X. (2021). Resurrecting the value premium. *The Journal of Portfolio Management*, 47(2):63–81.

[33] Bohn, H. (1998). The behavior of u.s. public debt and deficits. *The Quarterly Journal of Economics*, 113(3):949–963.

[34] Bohn, H. (2008). The sustainability of fiscal policy in the united states. *Sustainability of Public Debt*, pages 15–49. Reinhard Neck and Jan-Egbert Sturm, MIT Press, Cambridge, MA.

[35] Bomfim, A. (2003). Pre-announcement effects, news effects, and volatility: Monetary policy and the stock market. *Journal of Banking Finance*, 27(1):133–151.

[36] Boudoukh, J., Michaely, R., Richardson, M., and Roberts, M. (2007). On the importance of measuring payout yield: Implications for empirical asset pricing. *Journal of Finance*, 62(2):877–915.

[37] Brogaard, J. and Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science*, 61(1):3–18.

[38] Campbell, J. Y. and Shiller, R. J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. *The Review of Financial Studies*, 1(3):195–228.

[39] Campbell, J. Y. and Vuolteenaho, T. (2004). Bad beta, good beta. *American Economic Review*, 94:1249–1275.

[40] Change, Y., Kwak, B., and Qui, S. (2021). U.s. monetary and fiscal policy regime changes and their interactions. Halle Institute for Economic Research (IWH) Discussion Paper.

[41] Chatziantoniou, I., Duffy, D., and Filis, G. (2013). Stock market response to monetary and fiscal policy shocks: Multi-country evidence. *Economic Modelling*, 30(C):754–769.

[42] Chava, S. and Hsu, A. (2020). Financial constraints, monetary policy shocks, and the cross-section of equity returns. *The Review of Financial Studies*, 33(9):4367–4402.

[43] Chen, S. S. (2007). Does monetary policy have asymmetric effects on stock returns? *Journal of Money, Credit and Banking*, 39(2-3):667–688.

[44] Christie, S. (2005). Is the sharpe ratio useful in asset allocation? MAFC Research Papers 31. Applied Finance Center, Macquarie University.

[45] Cochrane, J. H. *The Fiscal Theory of the Price Level.* Princeton University Press, 2023.

[46] Cohen, R. B., Polk, C., and Vuolteenaho, T. (2003)). The value spread. *Journal of Finance*, 58(2):609–641.

[47] Czasonis, M., Kritzman, M., and Turkington, D. (2020a). Addition by subtraction: A better way to forecast factor returns (and everything else). *The Journal of Portfolio Management*, 46(8):98–107.

[48] Czasonis, M., Kritzman, M., and Turkington, D. (2020b). The relative importance of fiscal and monetary policy: An empirical perspective. MIT Sloan School Working Paper 6152-20.

[49] Czasonis, M., Kritzman, M., and Turkington, D. (2023). Relevance-based prediction: A transparent and adaptive alternative to machine learning. *The Journal of Financial Data Science*, 5(1).

[50] Daniel, K. and Titman, S. (1997). Evidence on the characteristics of cross sectional variation in stock returns. *Journal of Finance*, 52(1):1–33.

[51] Daniel, K., Hirshleifer, D., and Subrahmanyam, A. (1997). A theory of overreaction, self-attribution, and security market under- and over-reactions. *Journal of Finance*, 53:1839–1885.

[52] Darrat, A. F. (1990). Stock returns, money, and fiscal deficits. *The Journal of Financial and Quantitative Analysis*, 25(3):387–398.

[53] De Bondt, W. F. M. and Thaler, R. (1985). Does the stock market overreact? *Journal of Finance*, 40(3):793–805.

[54] Desai, H., Rajgopal, S., and Venkatachalam, M. (2004). Value-glamour and accruals mispricing: One anomaly or two? *The Accounting Review*, 79(2):355–385.

[55] Detzel, A. (2017). Monetary policy surprises, investment opportunities, and asset prices. *The Journal of Financial Research*, 40(3):315–348.

[56] Ehrmann, M. and Fratzscher, M. (2004). Taking stock: Monetary policy transmission to equity markets. *Journal of Money, Credit and Banking*, 36(4):719–737.

[57] Fama, E. F. and French, K. R. (1988). Permanent and temporary components of stock prices. *Journal of Political Economy*, 96(2):246–273.

[58] Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47(2):427–465.

[59] Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 75(3):3–56.

[60] Fama, E. F. and French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance*, 51(1):55–84.

[61] Fama, E. F. and French, K. R. (2007a). The anatomy of value and growth stock returns. *Financial Analysts Journal*, 63(6):44–54.

[62] Fama, E. F. and French, K. R. (2007b). Migration. *Financial Analysts Journal*, 63(3):48–58.

[63] Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

[64] Fama, E. F. and French, K. R. (2021). The value premium. *The Review of Asset Pricing Studies*, 11(1):105–121.

[65] Fama, E. F. and Schwert, G. W. (1977). Asset returns and inflation. *Journal of Financial Economics*, 5(2):115–146.

[66] Fama, E. F., Fisher, L., Jensen, M. C., and Roll, R. (1969). The adjustment of stock prices to new information. *International Economic Review*, 10(1):1–21.

[67] Gerakos, J. and Linnainmaa, J. T. (2018). Decomposing value. *The Review of Financial Studies*, 31(5):1825–1854.

[68] Goncalves, A. S. and Leonard, G. (2023). The fundamental-to-market ratio and the value premium decline. *Journal of Financial Economics*, 147(2):382–405.

[69] Gormsen, N. and Lazarus, E. (2019). Duration-driven returns. *Journal of Finance*. Forthcoming.

[70] Harvey, C. R. and Liu, Y. (2015). Backtesting. *The Journal of Portfolio Management*, 42(1):13–28.

[71] Hodges, J. L. (1958). The significance of the smirnov two-sample test. *Ark. Mat.*, 3:469–486.

[72] Ilmanen, A., Israel, R., Lee, R., Moskowitz, T. J., and Thapar, A. (2021). How do factor premia vary over time? a century of evidence. *Journal of Investment Management*, 19(4):15–57.

[73] Inker, B. (2022). Part 1: The value opportunity updated *and* part 2: Time to dive deep into value. GMO Quarterly Letter 3Q 2022.

[74] Ippolito, F. and Ozdagli, A. (2018). The transmission of monetary policy through bank lending: The floating rate channel. *Journal of Monetary Economics*, 95(C):49–71.

[75] Israel, R., Laursen, K., and Richardson, S. (2021). Is (systematic) value investing dead? *The Journal of Portfolio Management*, 47(2):38–62.

[76] Jaeger, A. and Schuknecht, L. (2007). Boom-bust phases in asset prices and fiscal policy behavior. *Emerging Markets Finance and Trade*, 43(6):45–66.

[77] Jansen, D. W., Li, Q., Wang, Z, and Yang, J. (2008). Fiscal policy and asset markets: A semiparametric analysis. *Journal of Econometrics*, 147(1):141–150.

[78] Jensen, G. R. and Mercer, J. M. (2002). Monetary policy and the cross-section of expected stock returns. *The Journal of Financial Research*, 25(1):125–139.

[79] Jensen, T. I., Kelly, B. T., and Pedersen, L. H. (2021). Is there a replication crisis in finance? *Journal of Finance*. Forthcoming.

[80] Kazemi, M. (2022). Intangible investment, displacement risk, and the value discount. MIT/ASU Working Paper.

[81] Kessler, S., Scherer, B., and Harries, J. P. (2020). Value by design? *The Journal of Portfolio Management*, 46(2):25–43.

[82] Kinlaw, W., Kritzman, M, and Turkington, D. (2021). A new index of the business cycle. *Journal of Investment Management*, 19(3):4–19.

[83] Kinlaw, W., Kritzman, M., Metcalfe, M., and Turkington, D. (2023). The determinants of inflation. MIT Sloan School Working Paper 6730.

[84] Kurov, A. (2010). Investor sentiment and the stock market's reaction to monetary policy. *Journal of Banking Finance*, 34(1):139–149.

[85] Kurov, A. and Stan, R. (2018). Monetary policy uncertainty and the market reaction to macroeconomic news. *Journal of Banking Finance*, 86(C):127–142.

[86] Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the fed funds futures markets. *Journal of Monetary Economics*, 47(3):523–544.

[87] Kydland, F. E. and Prescott, E. C. (1977). Rules rather than discretion: The inconsistency of optimal plans. *Journal of Political Economy*, 85(3):473–492.

[88] Lakonishok, J., Shleifer, A., and Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *Journal of Finance*, 49(5):1541–1578.

[89] Laopodis, N. T. (2009). Fiscal policy and stock market efficiency: Evidence for the united states. *The Quarterly Review of Economics and Finance*, 49(2):633–650.

[90] Lettau, M. and Wachter, J. (2007). Why is long-horizon equity less risky? *Journal of Finance*, 62(1):55–92.

[91] Litzenberger, R. H. and Ramaswamy, K. (1979). The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence. *Journal of Financial Economics*, 7(2):163–195.

[92] Liu, Y. (2023). Government debt and risk premia. *Journal of Monetary Economics*.

[93] Lo, A. W. (2002). The statistics of sharpe ratios. *Financial Analysts Journal*, 58(4):36–52.

[94] Loughran, T. and Wellman, J. W. (2011). New evidence on the relation between the enterprise multiple and average stock returns. *Journal of Financial and Quantitative Analysis*, 46(6):1629–1650.

[95] Lucca, D. O. and Moench, E. (2015). The pre-fomc announcement drift. *Journal of Finance*, 70(1):329–371.

[96] MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature*, 35(1):13–39.

[97] Mahalanobis, P.C. (1936). On the generalised distance in statistics. *Proceedings of the National Institute of Sciences of India*, 2(1):49–55.

[98] Mauro, P., Romeu, R., Binder, A., and Zaman, A. (2015). A modern history of fiscal prudence and profligacy. *Journal of Monetary Economics*, 76:55–70.

[99] McLean, R. D. and Pontiff, J. (2016). Does academic research destroy stock return predictability? *Journal of Finance*, 71(1):5–31.

[100] Neuhierl, A. and Weber, M. (2017). Monetary momentum. CESifo Working Paper Series 6648.

[101] Newey, W. K. and West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703–708.

[102] Nyholt, D. R. (2004). A simple correction for multiple testing for single-nucleotide polyorphisms in linkage disequilibrium with each other. *The American Journal of Human Genetics*, 74(4):765–769.

[103] Ozdagli, A. and Velikov, M. (2020). Show me the money: The monetary policy risk premium. *Journal of Financial Economics*, 135(2):320–339.

[104] Peters, R. and Taylor, L. A. (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics*, 123(2):251–272.

[105] Rigobon, R. and Sack, B. (2004). The impact of monetary policy on asset prices. *Journal of Monetary Economics*, 51(8):1553–1575.

[106] Riondato, M. (2018). Sharpe ratio: Estimation, confidence intervals, and hypothesis testing. Two Sigma Technical Report 2018-001.

[107] Romelli, D. (2022). The political economy of reforms in central bank design: evidence from a new dataset. *Economic Policy*, 37(112):641–688.

[108] Rosenberg, B., Reid, K., and Lanstein, R. (1985). Persuasive evidence of market inefficiency. *The Journal of Portfolio Management*, 11(3):9–16.

[109] Rudebusch, G. D. (1995). Federal reserve interest rate targeting, rational expectations, and the term structure. *Journal of Monetary Economics*, 35(2):245–274.

[110] Schwert, G. W. (1981). The adjustment of stock prices to information about inflation. *Journal of Finance*, 36(1):15–29.

[111] Shumway, T. (1997). The delisting bias in crsp data. *Journal of Finance*, 52(1):327–340.

[112] Tagkalakis, A. (2011a). Asset price volatility and government revenue. *Economic Modelling*, 28(6):2532–2543.

[113] Tagkalakis, A. (2011b). Fiscal policy and financial market movements. *Journal of Banking Finance*, 35(1):231–251.

[114] Taylor, J. B. (1993). Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy*, 39:195–214.

[115] Thorbecke, W. (1997). On stock market returns and monetary policy. *Journal of Finance*, 52(2):635–654.

[116] White, H. (2000). A reality check for data snooping. *Econometrica*, 68(2):1097–1126.

[117] Wu, J. C. and Xia, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3):253–291.