Systematic Investing in U. S. Banks: An Almost 27% Return Opportunity

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High, risk-adjusted returns are achievable by investing systematically in the U.S. commercial banking sector. To demonstrate what it looks like to invest in banks systematically, I designed an algorithm and applied it to an investable universe of about 200 banks to establish dollar-neutral, long/short portfolios beginning in 2006. With one parsimonious model, I achieved a 26.9% CAGR through year-end 2017, while maintaining relatively low volatility.

Synchronicity Can be Deceptive

Banks tend to follow patterns and trade in a group because, in comparison to many other sectors, banks are homogeneous and highly macro-dependent. In fact, only utility companies as a sector, historically exhibit lower dispersion.

In some ways commercial banks are like a school of fish. Schools of fish move so synchronously that until recently scientist thought that they were "egalitarian, leaderless units." However, using high-speed cameras, researchers discovered that each fish in a school bases its decisions on where to go not on the behavior of its nearest neighbors, as was previously assumed, but "on a synthesis of where all the fish in its field of view are headed."

While fish follow currents, light, heat, and food sources, banks respond to the economic environment, interest rates, investor sentiment and, more recently, to the long/short market dynamics influenced by passive investing and smart beta funds. So—yes—bank valuations ebb and flow as a group. However, like fish schools, this ebb and flow isn't as synchronous as first seems.

Thinking of banks in this way contributes to disciplined investing in the sector. It's important for investors to realize and balance the facts that the baking sector is macro dependent, exhibits very low dispersion, poorly compensates for idiosyncratic risks, yet is not so synchronous to warrant purely indexed investing. There is significant alpha to be earned by balancing these truths.

Thanks to the folks at S&P Global Market Intelligence, I've been able apply their amazing Clarifi® factor backtesting and simulation tool to test my views on how bank stock prices respond to the market environment and the degree to which the lack of synchronicity creates opportunities to extract excess returns while using a disciplined, systematic approach to investing.

The Opportunity

Depending on your liquidity requirements, there are more or less 200 investable commercial banks in the U.S. That's almost $2 trillion in investable market cap. Employing a systematic approach in the way described in this post opens up the investable universe and brings a top-down discipline that guards against the psychological and behavioral traps that tend to lead to poor selection of idiosyncratic risks. Even though relatively-low dispersion tends to under compensate bank investors for assuming idiosyncratic risks, many bank investors accept significantly more idiosyncratic risk than necessary—thereby adding unnecessary volatility to their bank portfolios.

The return summarized in the following discussion was generated by employing a factor-based approach to buy "value" and short into degrading credit quality or excessive valuation (depending on the regime).

My use of factors in this article is not intended to conform to any academic approach to factor-based investing. Factors are designed and employed here solely to add a systematic discipline to a fundamentally intuitive investing approach.

I haven't in this article given the exact specifications of the factors I designed for this exercise. The specifications of the proprietary factors that signal buy and sell decisions are based on more-than 25 years of fundamental analytical experience combined with a deep understanding of the available data and the techniques necessary to use this data to design and exploit sector-specific, proprietary factors. Anyone interested in learning more, feel free to contact me.

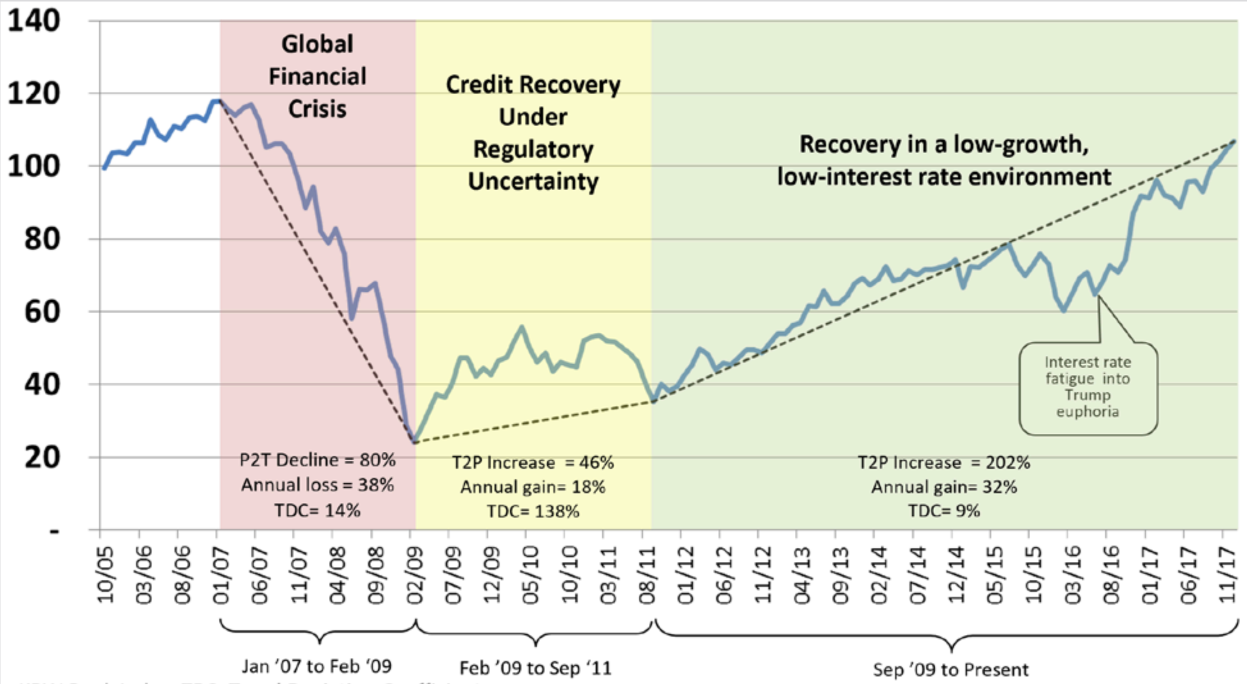
Caveat

This summary is designed to demonstrate the *baseline* capability of a systematic factor-based algorithm for investing in U.S. commercial banks. It is limited in its application in that it does not take account of transaction costs or market impact pricing effects (both of which erode returns). A reasonable attempt was made to include only banks for which liquidity is sufficient to build positions large enough to establish a $100 million portfolio.

Although not the subject of this post, liquidity challenges could be addressed in several ways. First with increasingly sophisticated modelling, investment decisions could cascade down a decision tree that optimizes the tradeoffs between model score and market effect related to liquidity. This approach would enhance the liquidity and capacity of the backtest; but it would also complicate the model and dilute the main points of this post. In execution, a good fundamental analyst paired with a competent trader could adapt the primary strategy to account for the liquidity tradeoffs. In either case, the strategy would reliably preserve capital and achieve high risk-adjusted returns.

The Last Decade: A Perfect Laboratory

Chart 1: Three distinct regimes for banks in the past decade.



KBW Bank Index, TDS=Trend Deviation Coefficient

Chart 1 divides the last decade or so into three distinct regimes that present obviously-different macro-investment environments for banks. The vivid differences among the three regimes for bank performance since 2006 would seem to challenge attempts to construct a uniform and systematic investing approach that could generate appealing risk-adjusted returns over the entire time. However, as explained below, a 26.9% CAGR return from 2006 through 2017 was achieved in backtesting a uniformly-applied, dollar neutral, long/short strategy over the entire time period (See Chart 2).

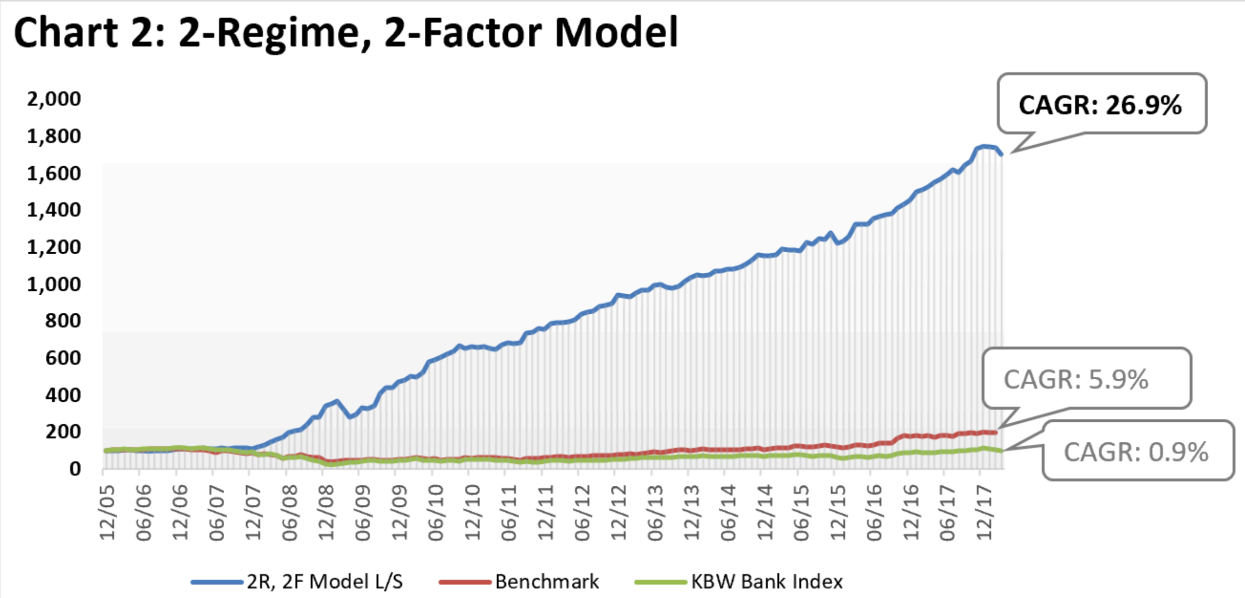


Chart 2 shows the results of investing $100 beginning in 2006 using my algorithm. The algorithm scores the investable universe and buys the banks scoring in the 80^{th} percentile and sells short those ranking within the 20^{th} percentile. The benchmark shown in Chart 2 is an equal-weighted long-only investment in the banks meeting the investable criteria in any given month.

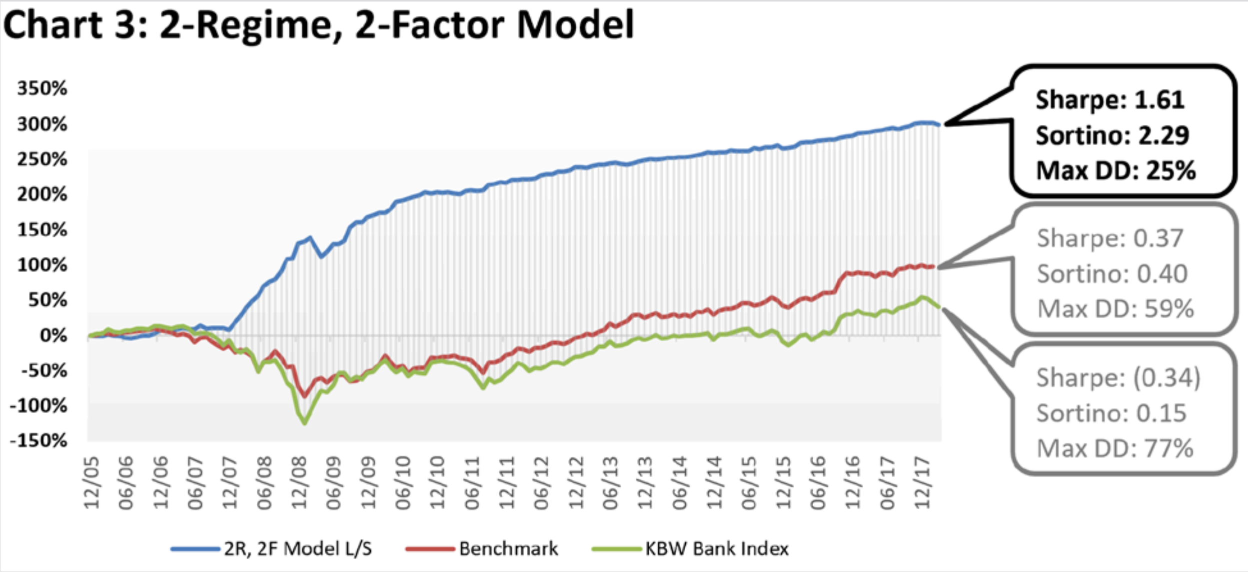
Model Regimes

I refer to the model as the 2-Regime, 2-Factor Model because the model executes in two stages and balances two factors. The first stage establishes whether the banking environment (the regime) is one of improving or deteriorating credit quality. The second stage weights the factors according to the credit regime, then scores each bank.

Far more work could have been done regarding the interest rate environment and yield-curve shape and the regulatory environment. These will remain the subject of future work. The goal of this exercise was systematic parsimony, and therefore, the model is constrained to considering only two proprietary factors related to credit and value.

While it's obvious from Chart 2 that the model significantly outperforms the benchmark and the KBW Bank Index, Chart 3 reveals more about the riskiness of the returns over the time period.

As shown in Chart 3, the model performs very well in terms of several standard measures of risk. The largest drawdown experienced by the model of 25% occurred between February and April 2009. Banks began to rally in February 2009 (the KBW Bank Index troughed in February 2009) as the market began to digest disclosures about how the TARP program was being implemented across the banking system and how it was being used to sure up asset prices.



The 2-R, 2-F model, however, did not exit the credit sensitive regime until October 2009 when the September 2009 Y-9 data became available. The September 2009 data showed that banks' ability to absorb predicted credit losses had inflected and was once again improving. As a result, *the 2-R, 2-F model was on the wrong side of the government-intervention-driven bank rally that kicked off in February of that year.*

Market events like this are cautionary and expose the risks of implementing a "set-it and forget-it" trading model. *Even the best data-driven models should be superintended by a strong fundamental analyst.*

From my vantage point as an investor at a large hedge fund deeply involved in the banking sector during the Global Financial Crisis (GFC), staying short throughout the crisis was a matter of maintaining a dispassionate eye on the data. Throughout the crisis, the market was eager to act on any signs that asset prices had bottomed. I remember listening to Angelo Mozilo who, during Coutrywide's third-quarter 2007 earnings call claimed, among other things, that the company's "profitability [would] be significant in the fourth quarter," and that he expected "10% to 15% ROEs for 2008." In after-market trading following the call, Countrywide rallied nearly 20%. While I had moments of doubt, I remained confident in the position because Washington Mutual had already reported and had taken a provision expense that was nearly twice the magnitude of Countrywide's after "normalizing" the provision expenses across the two companies. And as we all know, even Wamu's provision proved insufficient ultimately.

By December of 2008, we believed that, given government intervention in the markets for housing-related assets, we were nearing the trough in asset prices despite continued asset-quality deterioration. We purchased a 24.9% stake in the failed IndyMac FSB, which "with losses of about $12 billion, remains the most expensive failure in FDIC history," for 58 cents on the dollar.

Regime Detection

There are macro signals that inform when a portfolio of bank stocks should take on a tilt toward one factor or another and to what degree that tilt should be engaged. In this case, lagged, backward-looking (no look-ahead bias) Y-9 data for the entire U. S. commercial banking universe were aggregated to assess trends in overall credit quality. The aggregate environment is assessed using a computation that is a banking-credit analog to an Altman Z score. Minor trends in credit that are not yet significant enough to threaten future earnings are ignored. Once a trend is established, however, it triggers the model to balance the factors for investing in a credit-sensitive market. When not in a credit-sensitive environment, the model only acknowledges credit risk when it becomes significant for an individual bank (which is a significantly higher threshold).

The tricky part of this exercise is identifying the beginning of a credit cycle early enough to reposition the short side of the portfolio in time to benefit from the future deterioration in credit. There are a number of effective techniques for accomplishing this objective: outlier analysis, vintage analysis, or macro-based analysis (either macro-economic or sector-aggregate). In practice, all of these methods would be used to assess the credit environment and position the portfolio. For purposes of this exercise, sector-aggregate, macro-based measures were used to determine the credit environment.

There were several "false positives" revealed in retrospect with the technique employed to assess whether credit risk was improving or deteriorating in the model. Because I used Y-9 data, these type-1 errors persisted for at least three months until Y-9 data were available again. No doubt, these false positives hurt performance; but in calibrating the model to the credit environment, it is clear that a type-1 error is significantly less detrimental to model performance than a type-2 error.

Historically, once the market becomes credit sensitive, credit quality and risk matter significantly earlier than when the market isn't sensitive to credit quality generally. Once the market is sensitive to credit, it's usually difficult to rebalance. The global GFC was historically atypical in that "short" opportunities continued to exist through successive attempts of the market to believe in a floor under the deterioration of credit and asset prices.

Model Structure

Image 1: Summarized Model Structure

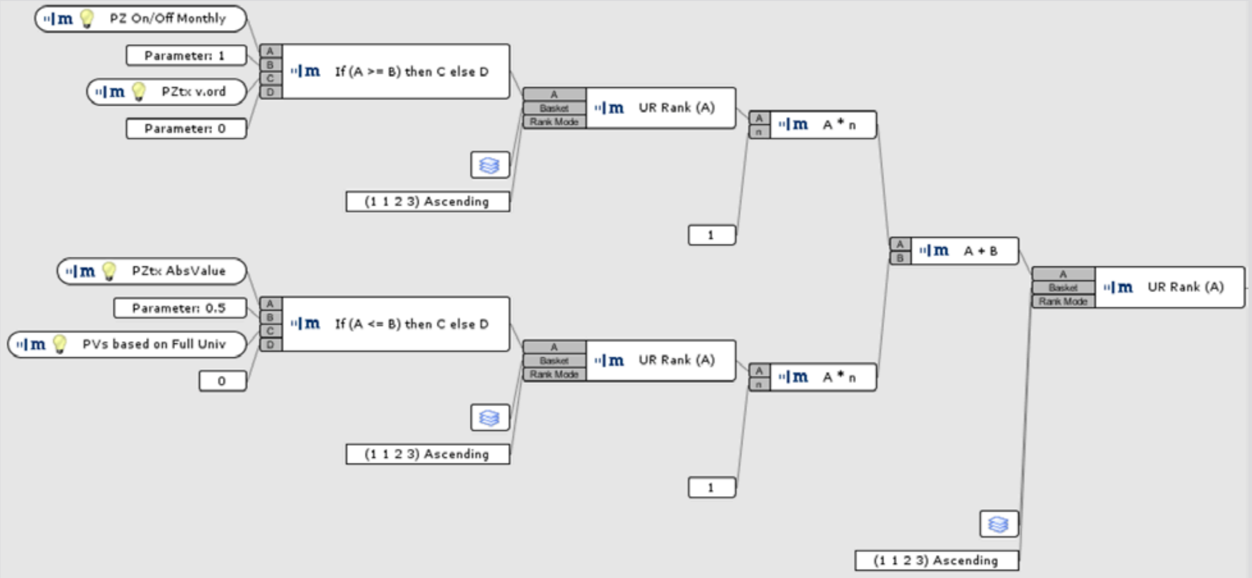


Image 1 is the summary model executed in Clarifi® (it is an actual screenshot from the Clarifi® work environment). The top half of the tree through-passes the high-sensitivity credit deterioration factor to each company's score when the rebalancing period is identified as occurring within a credit deteriorating environment. The bottom half of the tree scores banks on "value" so long as the bank being scored doesn't have significant credit issues.

For purposes of this exercise, "value" is assessed based on estimating each bank's one-year forward return on tangible common equity (1YFwrdROTCE) and its current price to its estimated one-year forward tangible common equity (P/1YFwrd TCE). Each month, the model regresses these components and calculates an expected value for every bank in the investable universe that month. If not in a credit deteriorating environment, and if the individual company doesn't have significant credit issues, the most under-valued banks are purchased, and the most over-valued banks are sold short.

Generally, the relationship between some measure of return on capital and price to capital is a durable indicator of value in the banking sector. However, there are several unique ways to specify this general relationship that are more or less effective depending on—among other things—the specific characteristics of the investment environment, the stage of the economic and credit cycle, and the shape of the yield curve shape. I will spend more time on this point in the next article.

There are sometimes debates about whether the relationship between price to book and return on equity is equivalent to assessing value based on the Price Earnings Ratio (P/E Ratio) (or inverted earnings yield). This relationship between these two concepts is conceptually accurate. The slope of a line relating P/B to ROE reduces to P/E after renaming "book" as "equity" and "return" as "earnings" (In other words, P/Equity divided by Earnings/Equity = P/Earnings). However, the relationship between earnings and value is more complex than what is captured in the simplest regression between these components, and my "value" factor captures significantly more of this additional complexity.

Summarizing the opportunity for systematically investing in U.S. commercial banks:

- With more than 200 investable commercial banks in the U.S., opportunities and market inefficiencies come and go all the time in this space. Few investors have the fundamental capacity to exploit them all when they arise, or—stated differently—the cost/benefit of exploiting these inefficiencies requires lowering cost significantly, and a systematic approach lowers cost a lot.
- In comparison to many other sectors, banks are relatively homogeneous. And given regulatory reporting requirements and standards, it's relatively easier to use machines to assemble comparable profiles that are reliable for investment purposes.
- That said, the available data is frequently misunderstood and misapplied by systematic or factor-based investors who don't understand banks and fail to recognize when bank data is either wrong or misleading. In fact, the proliferation of smart beta funds and other systematic investors allocating to financial companies may be a significant source of exploitable market inefficiencies relevant to bank stocks.
- My approach extracts trading signals and valuation information from the entire banking market as the market's valuation parameters are changing in real time. It exploits the lag that persistently exists between how the most liquid names respond to these real-time changes compared to less liquid names. Being able to respond quickly and reliably is the way to profit from this inefficiency.
- Protecting the downside with a tested quality screen allows the safety of avoiding value traps while buying cheap. Vast experience in failure-projection modeling and "hands-dirty" short selling is helpful in meeting this challenge.

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