Can the impact of contagion effects on global equities be reduced through a dynamic asset allocation strategy based on capital flows data?

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Abstract

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The literature supports evidence of a contagion effect, where an increase in correlations and price movements is observed across assets during a market downturn. This contagion effect can diminish the diversification expected from a portfolio's asset allocation. There is research showing a connection between capital flows and contagion. This thesis considers this connection through a dynamic allocation strategy with allocation decisions based on capital flow movements. This strategy is applied to an equity-only portfolio with the objective of maintaining some benefits of diversification while preserving capital. In an out of sample test, a regime switching model is used to predict market downturns for the period from January 1998 to December 2018. For the predicted downturns, portfolios' geographical allocation is altered with allocation changes based on the countries' capital flows. Results from historical back tests show weak evidence of higher returns and similar Sharpe ratios for a dynamic strategy versus a static strategy for portfolios of developed market equities. The implications for portfolios of emerging market equities are less obvious.

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1. INTRODUCTION

There are a number of studies supporting the existence of contagion, defined as a significant increase in cross market correlations and price movements (volatility) during a market downturn. This change in correlations between assets has an impact on asset allocation decisions as the benefits of diversification appear to be reduced. If they are able to forecast regime shifts, investors might implement a dynamic asset allocation strategy to account for the changes incurred and mitigate some effects of contagion. There is research suggesting a connection between contagion and capital flow movements. These studies, reviewed in Section 2 of the thesis, suggest countries impacted by contagion experience a surge in capital flows prior to a downturn, followed by a sudden stop in flows as the downturn occurs. The research posits that this effect is driven by investor herding behavior that is unrelated to the fundamentals. Equipped with this knowledge, an investor may be able to exploit the link of contagion with capital flows using a dynamic asset allocation strategy. If successful, this could help preserve capital and limit the negative impacts on the level of diversification achieved by an equity portfolio during a downturn. In this thesis, I attempt to evaluate the benefits of such a strategy.

Many of the articles examining dynamic strategies focus on allocation decisions across asset classes; whereas, this study considers geographic allocation within an international equity portfolio. I propose a dynamic allocation strategy and test a portfolio of equities in an effort to lower the impact of contagion on diversification during a market downturn. To predict the downturns, I use a Markov regime-switching model relying on financial economic indicators. For the predicted downturn periods, geographical allocation decisions are based on capital flows data. While most research has focused on either developed or emerging markets, this study considers both.

There is some weak evidence to support the implementation of the dynamic strategy for a portfolio of developed market equities. Although the differences are not statistically significant, the results from an out of sample test covering the period from January 1998 to December 2018 show a slightly higher return for the dynamic strategy versus the static one.

This study contributes to the research on contagion by examining the connection between capital flows and downturns and whether this information can be used to relieve the effects of contagion. Making geographical allocation decisions based on capital flows helps to verify the importance of capital flows in the transmission of contagion across countries. As the transmission of contagion is typically observed through correlated movements in global equities, my research considers a portfolio of equities only. By analysing a portfolio of developed and emerging market equities, I consider how an investor can diversify within equities to reduce contagion risks. A focus on equities contributes to the literature on dynamic asset allocation which often diversifies across different classes of assets rather than within equities.

The paper proceeds as follows: Section 2 reviews the literature on contagion, its links to asset allocations and capital flows. The hypothesis is presented in section 3. Section 4 discusses the data and methodology. Section 5 presents and discusses the results. Section 6 concludes.

2. REVIEW OF THE RELEVANT LITERATURE

2.1 Evidence of Contagion

In a study focused on the Asian crisis, Forbes and Rigobon (2002) find evidence supporting "no contagion, only interdependence", suggesting correlation movements are proportional to expectations and that previous research on contagion contains a bias towards finding a contagion result due to a heteroscedasticity problem. Evidence from subsequent articles supports the existence of contagion when accounting for heteroscedasticity. During the Asian crisis (the same crisis as studied in Forbes and Rigobon), Corsetti, Pericoli and Sbracia (2005) find evidence of contagion from Hong Kong to five other markets (Singapore, the Philippines, Italy, France and the U.K.) using a single factor model of stock returns. Similarly, Chiang, Jeon and Li (2007) find evidence of contagion effects during the Asian crisis from examining heteroscedasticity-adjusted correlations and dynamic conditional correlations. Kenourgios, Samitas and Paltalidis (2011) find contagion from the source country using a regime switching Gaussian copula model and asymmetric generalized dynamic conditional correlations for three events occurring between 1997 and 1998 (Asian crisis, Russian crisis, and Brazilian stock market crash), the 2000 tech bubble, and the 2002 Brazilian crisis. Bekaert, Ehrmann, Fratzscher and Mehl (2014) find evidence of contagion using a factor interdependence model during the global financial crisis of 2009. Their model shows that contagion cannot be explained by interdependence alone, and must be accounted for explicitly. Boubaker, Jouini and Lahiani (2016) use cointegration techniques, Granger causality tests, impulse response functions and variance decompositions to investigate contagion during the financial crisis. Consistent with Bekaert et al. (2014), they find significant evidence of contagion effects between the U.S. stock market and other developed and emerging countries.

2.2 Impact of Contagion on Asset Allocation Decisions

Investigating the impact of contagion on portfolio decisions, Das and Uppal (2004) create a model of international equity returns capturing sudden price swings with simultaneous increases in correlations. Using this model, they determine optimal portfolio weights[1] and compare those weights to the optimal weights derived from a model without price jumps. Results show how the contagion effect impacts allocation decisions. Accounting for the contagion effect leads to different optimal allocations versus those derived when ignoring the effect. The benefits from diversification are slightly lowered, and there is a cost to investors' utility from ignoring the effect, regardless of the level of risk aversion. The results are notably different for developed versus emerging markets; with a stronger impact from emerging countries attributed to larger swings. In a similar approach, Ang and Bekaert (2002) use a regime-switching process to consider dynamic asset allocation choices. This process includes a normal regime with low correlations and volatilities, and a bear regime with higher correlations and volatilities. Evidence supports distinct allocations across the two regimes. Like Das and Uppal (2004), the results show that investors face a cost in utility for ignoring regimes. The authors conclude there is a benefit to international diversification since it is not optimal to simply allocate the entire portfolio to the lowest volatility asset. Focusing on just three developed markets (U.S., U.K. and Germany), Das and Uppal find that the optimal portfolio for the bear regime contains both U.S. and German equities. Building on this study, Ang and Bekaert (2004) use a regime switching model out-of-sample to exploit the regime changes through asset allocation decisions for a portfolio of 20 developed country equities grouped into six regions. The dynamic allocation decisions enhance portfolio performance with the regime dependent portfolio offering a better Sharpe ratio than both the market capitalization weighted portfolio and the non-regime dependent portfolio. The

[1] Appendix A compares the methods used to determine allocation weights in each study.

authors again conclude that the benefits of international diversification are not entirely lost during the bear regime, given that the optimal allocation includes several regions.

Work by Hauptmann, Hoppenkamps, Min, Ramsauer and Zagst (2014) and Kritzman, Page and Turkington (2012) also rely on Markov-switching regime models to predict regimes and adjust asset allocations accordingly. In both cases, the dynamic allocation decisions based on the regime shifts outperform a static strategy although more than just equity assets are considered. Solnik and Watewai (2016) also demonstrate the importance of accounting for the asymmetric characteristics of contagion in asset allocation decisions by incorporating diffusion and jumps with regime switching. Optimizing the portfolio allocation based on information from the model improves diversification and results in a higher Sharpe ratio.

2.3 Contagion and Capital Flows

There is research showing a connection between large capital flow movements and the high volatility periods typically associated with contagion. Fratzscher (2012), Rey (2015) and Forbes and Warnock (2012) establish a connection between capital flows and global factors, suggesting that capital flow movements are driven by global changes in risk. Fratzscher (2012) finds that movements in capital flows during the global financial crisis can be attributed to global factors, such as liquidity and risk. Rising risk results in a retrenchment of flows to emerging countries. Rey (2015) observes strong cyclicality in capital flows, pointing out the increasing importance of capital movements due to globalisation. Her analysis finds evidence of an important correlation between capital flows and market uncertainty, as measured by the VIX. When volatility is low, there are surges in gross capital flows and when volatility increases, capital flows are significantly smaller. Forbes and Warnock (2012) make a direct connection between capital flows and contagion. Looking at extreme movements in capital flows (where among other criteria, flows must be more than two standard deviations above or below a historical mean), these authors determine that contagion and increases in global risk explain extreme capital movements. More specifically, contagion and elevated risk are linked to “stops” (lower gross capital inflows) and “retrenchments” (lower gross capital outflows). Both of these types of extreme capital flow movements were common during the global financial crisis.

Interestingly, all three studies make the observation that the receipt of large capital flows by a country before a crisis can be an indicator for poor performance during the crisis. Fratzscher

(2012) finds that although countries with riskier fundamentals experienced larger capital outflows during the crisis, they also had higher inflows before the crisis, and during the recovery. Rey (2015) asserts that markets having greater credit flows are more likely to be affected by the global cycle and that significant credit growth during low volatility times is a good indicator for a crisis. Data on extreme capital flow events from Forbes and Warnock (2012) show that sudden surges tend to precede events that lead to sudden stops. Surges were observed before the Mexican crisis, the Asian crisis and the global financial crises. Both the Mexican crisis and the global financial crisis were followed by a stop in capital flows while the Asian crisis fell just short of meeting Forbes and Warnock's (2012) criteria to be labelled a stop.

Historical examples of a surge in capital inflows prior to a contagion event are provided by Kaminsky, Reinhart and Vegh (2003) as they investigate why some crises result in contagion. The authors consider four crises with contagion from the early 1990s (European Exchange Rate Mechanism crisis, Mexican crisis, Asian crisis and Russian crisis). These events experienced capital flow bubbles before the shock, and abrupt reversals leading to lower capital flows thereafter. Contrarily, shocks occurring in the following years (Brazilian devaluation in 1999, Turkish devaluation and Argentinian default in 2001) when capital flows remained low, did not result in contagion. Additionally, the reversal of capital flows into Latin America following Mexico's default in 1982 is cited as a reason why shocks in the following years experienced limited to no contagion effects. Kaminsky, Reinhart and Vegh's work concludes that capital flow movements are an important element for the occurrence of contagion.

Some evidence points to international investors as the drivers of the extreme capital flow movements leading to contagion. Using a mathematical model and an empirical example, Calvo and Mendoza (2000) demonstrate how globalization increases contagion by lowering investors' incentives to collect information and encouraging them to all hold a market portfolio. The example shows how tracking error and fixed costs of obtaining information are significant in inducing large capital outflows unrelated to specific country fundamentals. Boyer, Kumagai and Yuan (2006) investigate accessible and inaccessible markets during the 1997 Asian crisis where accessible markets are those available to foreign investors. Results show that the behavior of international investors influences contagion. Increases in correlations are more pronounced for accessible stocks and the effects on inaccessible stocks tend to lag accessible stocks. This supports the idea that crises spread first to accessible markets via foreign investor flows. Boyer makes the argument that movements in capital are not related to fundamentals but rather driven by asset holdings of international investors. Focusing on Latin America and the Mexican crisis, Calvo and Reinhart (1996) find that capital flows to larger, more developed and more open economies influence the flows to the surrounding, smaller economy countries and that countries whose equity markets are less accessible to foreign investors tend to be more shielded from crisis. Tong and Wei (2011) investigate how the volume and composition of capital flows affects the performance of manufacturing firms in emerging markets during the Global Financial crisis. Their findings show that firms having a stronger dependence on capital flows in the form of bank lending and portfolio flows tend to experience worse outcomes during the crisis; while firms with exposures to foreign direct investment flows are more insulated.

3. HYPOTHESIS

I hypothesize that the impact of contagion and its effect on diversification can be mitigated through a dynamic asset allocation strategy. With contagion being related to large capital flow movements, seemingly driven by investor behavior and unrelated to fundamentals, it can be expected that countries with capital flow surges would experience a sudden pull back on those flows during a downturn. There is evidence that these stops and retrenchments are cyclically related to global risk. As such, when uncertainty rises (as in a downturn), countries experiencing reduced capital flows are more likely to suffer contagion. Implementing a dynamic asset allocation strategy during a downturn, and basing the allocation decisions on capital flow movements should account for this contagion effect and help to mitigate it. Having regard for this, investors may potentially limit their exposure to the contagion effect through improved diversification and preservation of capital. This leads to the following hypothesis in its alternative form:

H_A: Implementing a dynamic asset allocation strategy based on countries' capital flow movements leads to better diversification and conservation of capital during a downturn for a portfolio of international equities.

4. DATA AND METHODOLOGY

The first step in testing my hypothesis is to predict market downturns. To do this, I use a two regime Markov-switching model inspired by Page, Kritzman and Turkington (2012). Markov-switching models are very commonly used for predicting changes in regime and the method employed by Kritzman et al (2012) is straightforward for working with historical data. The method applies the Baum-Welch algorithm, making use of the forward backward algorithm, to determine the probability of being in a given regime for each data observation. It is an iterative process converging to a maximum likelihood where the estimated regime probabilities best fit the observed data. In this study, the observed data are the OECD CLI. I programmed the model in Matlab, assuming two regimes. The first iteration relies on assumptions for the initial parameter values.[2] With these initial assumptions, I use the smoothing forward-backward algorithm to estimate the expectation of being in regime 1 or regime 2 for each observation. The forward and backward probability estimates account for past and future data observations (respectively) as well as the transition probabilities. For example, the forward probability of being in regime 1 for a given observation uses information from the previous observation and sums the probabilities of the two possible paths from this observation. That is, the probability of the previous observation having been in regime 1 and transitioning to regime 1 plus the probability of the previous iteration having been in regime 2 and transitioning to regime 1. This sum is then multiplied by the probability that the current observation is in regime 1. Backward probabilities are estimated in much the same way but rely on information from the future observations instead. The forward and backward probabilities are then smoothed by multiplying them together. All possible paths are accounted for using this algorithm. From these calculations, there is sufficient information to obtain new estimates for the parameter values of the initial probability of being in regime 1, the mean and standard deviation of each regime and the transition matrix. I use these newly estimated parameter values to repeat the process and calculate new expectations. At each iteration, a likelihood value[3] is calculated. The process is repeated as long as the difference in likelihoods across two iterations is greater than a threshold value of 0.00001. When the change in likelihood becomes less than 0.00001, the method

[2] See Appendix B for assumed values.

[3] The likelihood is calculated with the sum of the forward probabilities.

converges and the likelihood is considered maximized. The resulting regime probabilities are the best fit for the observed data.

As mentioned, the observed data for this thesis are Composite leading indicators (CLI), published monthly[4] by the Organization for Economic Cooperation and Development (OECD). CLI are designed to signal turning points in the business cycle. They are composed of economic variables that mimic the fluctuations in economic activity but precede the timing of those fluctuations. I use global and United States CLI to make two sets of regime predictions. The global CLI accounts for the 35 OECD member countries and 6 other countries (Brazil, China, India, Indonesia, Russia and South Africa). While the global CLI considers more countries, the U.S. CLI provides a longer history for the probability estimates, with data starting from January 1955 compared to November 1973 for the global CLI. I fit the model using the respective histories available for the U.S. CLI and global CLI up to December 1997. For each month going forward, the probability of being in regime 1 or regime 2 is estimated by re-calibrating the model with the growing range of data. These are the out of sample regime predictions (Tables 3 and 4), covering the period from January 1998[5] to December 2018. A downturn is identified when the probability of being in the downturn regime becomes greater than 60%[6] and ends on the month that the probability moves back below 60%. I employ a two-month lag in order to align with the actual publication timing of the OECD CLI data. The regimes are classified according to their means and volatilities, with the downturn regime characterized by a lower mean CLI value and higher volatility. The next section discusses the results of the predicted downturns.

I use the countries from the MSCI World and Emerging Market (EM) indices for my analysis. Their inclusion in the portfolio depends on the history of capital account data available. Of the 23 countries currently in the MSCI World Index, 17 countries have a complete data time series dating back to 1998. Eleven out of the 24 countries currently in the MSCI EM index have a 20-year history of capital flows. Table 1 lists the countries included in the portfolios. MSCI

[4] CLI data are published with a 2-month lag; e.g. the CLI number for January is only published in the month of March.

[5] Other out of sample starting points were considered, January 1995, 1996, 1997 and 1999 with little impact on the results. January 1998 was selected to avoid the issue of being in a downturn while moving from the in sample to the out of sample predictions. This provides a 20 year period for out of sample testing.

[6] Thresholds of 50% and 70% were also tested with little impact on results.

individual country indices are used for calculating portfolio returns. For those countries included in the portfolio, I calculate the returns using the MSCI individual country index returns multiplied by their corresponding market cap weights.

During the months where the probability of a downturn is less than 60%, each country's weight is equal to its beginning-of-the-month MSCI market cap[7] divided by the total market cap of the countries included in the portfolio. In months where a downturn is predicted, I apply changes to the geographical allocation of the equity portfolio. These changes remain in effect for the duration of the downturn with a one month lag.[8] These changes consist of reducing the weights for countries with capital flow surges during the predicted downturn periods. I define a capital flow surge according to criteria used by Forbes and Warnock (2012). A country is classified as having a surge in capital flows if, for the quarter corresponding to the first month of a predicted downturn, the year over year difference in capital flows is more than one standard deviation above the 5-year historical mean. Reducing the allocation for countries with capital flow surges is a defensive strategy based on my hypothesis that countries experiencing surges in their capital flows often experience lower returns during a downturn as these large flows, unrelated to fundamentals, are expected to halt. To test this hypothesis, I employ allocation reductions of 60% relative to the market cap weights. The 60% reduction is an arbitrary decision for illustrative purposes. Other reduction proportions were tested and the results were found to be aligned pro rata. The difference from the underweight is redistributed equally across the remaining countries in the portfolio. I calculate the portfolio returns by taking the weighted sum of the country allocations and their respective MSCI country index returns. To observe the impact of the defensive allocation changes, the portfolio returns with the reduced allocations are compared to portfolio returns with the MSCI country market cap weights (Tables 7 and 8).

[7] According to its MSCI Country Index

[8] A one-month lag is used since implementation of the allocation changes is not simultaneous with prediction of the downturn. Allocation changes occur in the month following the predicted start of the downturn and end one month after the predicted end of the downturn.

5. RESULTS

The in-sample parameter estimates for the two regimes are presented in Table 2. For both the global and U.S. CLI predictions, the regime having the lower mean and higher volatility is the downturn regime. The global CLI downturn regime has an average CLI value of 99.3 with a volatility of 0.83 compared to 100.7 and 0.40 for the normal regime. For the U.S. CLI estimates, the mean is 98.5 for the downturn regime with a volatility of 1.00 versus a 100.8 mean and 0.82 volatility for the normal regime. There is a high level of persistence present in both of the regimes, consistent with the idea that once in a regime, one is likely to remain there. The standard errors of the parameters show the mean and standard deviation to be significantly different across the two regimes. The persistence variables are also statistically significant.

To obtain the out of sample probability estimates, I re-calibrate the model for each monthly CLI value from January 1998 to December 2018. For each month's CLI value, the model estimates the probability of being in the downturn regime or the normal regime. A month is considered to be in the downturn regime when its probability is greater than 60%. The out of sample downturn predictions are presented in Tables 3 and 4. The model predicts five downturn regimes using the global CLI and four using the U.S. CLI. The first downturn forecast from the global CLI occurs between May 1998 and July 1999, which corresponds to the Russian default crisis and the Long Term Capital Management crisis. No downturn related to this period is predicted by the U.S. CLI. Downturn 2 from March 2001 to January 2004, is aligned with the tech bubble and is consistent with the first downturn predicted using the U.S. CLI (downturn A, February 2001 to December 2003). Downturns 3 and 5 from the global CLI (starting in August 2008 and March 2016, respectively) have similar starting points as second and fourth downturns (B and D) from the U.S. CLI (starting dates of October 2008 and February 2016), but with different ending points. For the downturns related to the global financial crisis (3 and B), global CLI predictions have a duration of 19 months compared to a 28-month duration from the U.S. CLI predictions. The longer duration from the U.S. CLI could be because the global financial crisis was U.S. centric. Downturn 5 closely follows the 2015 drop in crude oil prices. It is anticipated to end 7 months earlier than the corresponding downturn D predicted from U.S. CLI. The timing of downturns 4 and C are aligned with the 2013 taper tantrum where substantial volatility in U.S. bond yields spilled over to global stock markets. The U.S. CLI downturn C is expected to end before the global CLI predicted downturn 4 even begins and it has a shorter duration (7 months versus 16 months). The longer duration for the global CLI prediction may be explained by the considerable spillover effect felt by countries outside the U.S. (notably emerging markets); while the U.S. recovered quite rapidly.

Compared with the actual CLI turning points as provided by the OECD (Figures 1 and 2), the out of sample downturns predicted from my model capture each of the peak to trough events in the actual CLI turning points (5 events for the global CLI, 4 for the U.S.). The durations of the predicted downturns are also consistent. Downturn C from the U.S. CLI predictions is the exception to the late timing as it predicts a downturn before the actual OECD turning point. Comparing predicted downturns to returns for the MSCI World and Emerging Market Indices (Tables 3 and 4) also shows a lag present relative to market movements. For the predictions from the global CLI, a noteworthy portion of the drawdown in equities is captured in downturns 1, 2 and 3; but downturns 4 and 5 start late, mostly capturing the rise in equity prices. From the U.S. CLI downturn predictions, the decline in equities is captured in downturns A, B and C, but the last downturn from this series also coincides more with the recovery. The duration of each of the predicted downturns often encompasses the start of the recovery for market returns. This is reflected in the mostly positive static portfolios returns for each of the downturn periods (Tables 7 and 8). While this method may predict a downturn in a timely manner, it appears less optimal for predicting the start of the recovery.

The in sample global and U.S. CLI predictions also exhibit lagged results compared to the actual CLI turning points (Figures 3 and 4). Two of the actual U.S. turning points are not captured by the in sample U.S. downturn predictions. These two instances refer to flash crashes with relatively shorter term economic impacts. The influence of such events is likely lessened by the smoothing feature of the forward backward algorithm used in predicting downturns. U.S. CLI also have a longer history available compared to the global CLI, which can also reinforce the smoothing issue for the U.S. in sample predictions relative to the global CLI predictions. The global CLI in sample predicted downturns capture all of the peak to trough events as reported in the actual turning points for global CLI.

The countries experiencing a capital flow surge during the predicted downturns are listed in Tables 5 and 6. Their weights in the portfolio are reduced for the duration of the downturn. Due to a lack of historical data, the emerging market countries are excluded from the analysis of downturn 1. I apply the underweights only during the predicted downturn months. For all other months, a country's weight is its market cap proportion from its respective MSCI index.[9] The Dynamic portfolio refers to the portfolio with the underweighted country allocations. The Static portfolio uses the proportional market cap weights for the full period.

Out of sample results for the Dynamic and Static portfolios are shown in Tables 7 and 8. Although the differences in return and volatility are not found to be statistically significant across the two portfolios (Tables 9 and 10), the historical out of sample test shows instances where the dynamic portfolio helps preserve capital. For both global and U.S. CLI predicted downturns, the Dynamic portfolio has a higher annualized return than the Static portfolio over the full out of sample period for the developed markets. The Dynamic portfolio also has lower volatility and a higher Sharpe ratio. While the Dynamic portfolio does not have a higher return over the full period for the emerging market countries, it does have a lower volatility and a better maximum drawdown[10]. Results are similar for the individual downturn periods. For the downturn predictions from the global CLI, the Dynamic portfolio has a higher return in four out of the five downturns[11] for the developed markets but in only one of the downturns for the emerging markets. The largest positive difference occurs in Downturn 2 for the developed markets. This downturn is aligned with the tech bubble. For this period, the Dynamic portfolio yields an annualized return of 2.56% with a volatility of 16.30%, compared to a 0.86% return and a 16.91% volatility for the Static portfolio. The dynamic portfolio also has a higher Sharpe ratio (0.13 versus 0.03) and improved maximum drawdown (-33.19% vs. -34.92%). For the emerging market countries, the Dynamic portfolio has a marginally higher annualized return (1.41% vs. 1.26%) only during the global financial crisis (downturn 3). The standard deviation and Sharpe ratio are near equal. However, Downturn 1 is excluded from the emerging markets analysis[12] and no weight changes are applied in Downturn 4. For the out of sample results from the U.S. CLI estimates, the developed markets Dynamic portfolio has a higher mean return in 3 of the 4

[9] In downturns 4 and C, none of the emerging market countries were experiencing capital flow surges so the EM portfolio weights remain unchanged from the market cap for these downturns.

[10] Maximum drawdown is the greatest loss from a peak to a trough before a new peak is attained.

[11] Special case for downturn 3 returns are nearly equal, the dynamic portfolio outperforms by 0.004%.

[12] Downturn 1 is excluded for the emerging markets as there is not sufficient data to calculate the 5-year historical mean of the capital flow changes.

downturns. The maximum drawdown is improved for those same three downturns (A, C and D) and the volatility of the Dynamic portfolio is lower in all cases. Once again, the downturn related to the tech bubble (downturn A) has the strongest relative performance for the Dynamic portfolio, earning an annualized return of -0.40% and a standard deviation of 16.68% compared to a -1.97% return and 17.44% volatility for the Static portfolio. Results for the emerging markets are less favorable. The dynamic portfolio has a lower annualized return for each of the U.S. CLI predicted downturns. Since, none of the countries for downturn C is in a capital flow surge, the dynamic and static portfolios hold the same weights over the period. This is a contrast to results for the global CLI predictions where the dynamic strategy did have a higher annualized return for the emerging market portfolio during the global financial crisis downturn. The result is not reproduced for the U.S. CLI global financial crisis downturn, downturn B, likely because the length of the downturn captures the start of the recovery. Downturn B lasts 28 months while downturn 3 is 19 months long. As previously mentioned, because the global financial crisis was U.S. centric, it is possible the global CLI predicts a shorter downturn regime due to an earlier recovery for some of the countries in its composition.

With the observed p-values, I fail to reject that the returns or volatilities are equal across the two portfolios for all the out of sample results (Table 9). I find only the Sharpe ratios for the developed market portfolios in downturns 5 and C and the emerging market portfolio for the full period from global CLI to be significantly different. This is likely explained by the minor weight changes applied to the countries. Depending on the original weight the surge country has in the index, the reduced allocation could have little impact. There are also few countries deemed to have capital flow surges and thus having reductions to their allocations. For the small sample of emerging countries, there are even fewer weight changes which could explain the weaker dynamic portfolio performances observed for the emerging markets relative to the developed markets.

6. CONCLUSION

This thesis finds that a dynamic asset allocation strategy based on capital flows provides some performance benefits for the portfolio of developed market equities. Although the differences in returns are not statistically significant across the two portfolios for any of the downturns, the out of sample tests with the global CLI show that for the developed countries, implementing the Dynamic portfolio would have yielded higher returns over the full period and in four out of five predicted downturns. The Sharpe ratios are at least as high as that of the Static portfolio and the Sharpe ratio is statistically higher for Downturn 5. For the out of sample U.S. predictions, the Dynamic portfolio yields a higher annualized return over the full period and in three out of the four predicted downturns and the Sharpe ratio is improved for all downturns. For the emerging markets, the Dynamic portfolio return is only higher for downturn 3, the Global financial crisis. This suggests that capital flows might be more informative for developed countries.

The limited weight changes applied in the model used in this thesis might explain why the differences in results are not statistically significant across the two portfolios. Few countries are defined as having capital flow surges; especially in the emerging markets. This means that the portfolio weights of the dynamic and static strategies may not be substantially different. Using a different measure of capital flows, or adjusting the criteria for defining a surge could have an impact on the number of countries selected for underweighting, which, in turn, could affect the significance of the results. Data availability is a considerable challenge for emerging markets. Of the 24 countries in the MSCI EM index, only eleven had a long enough history of capital flow data for the analysis conducted in this thesis. This gives a smaller initial set of emerging market countries considered for reduced allocation which could also contribute to why the developed markets portfolio allocations show stronger results.

Although the regime predicting methodology does a reasonable job at capturing the peaks and troughs of the actual CLI data, there is a visible lag in the predictions. The choice of the global and U.S. CLI as the input data for the predictions may influence this. Although the global CLI accounts for some emerging countries, it is mostly composed of information regarding developed countries. Using CLI from the emerging countries that make up the portfolio could be a more accurate reflection of the economic state of those countries, leading to improved downturn predictions. It is also important to note that the results for the developed markets are stronger for the downturns predicted with the U.S. CLI. This could be attributed to the U.S. economy being a driver of the global economy and thus a better predictor of market downturns for developed countries. Returns for both the developed and emerging markets portfolios might improve with a more accurate prediction of downturns.

Overall, the analysis presented in this thesis provides some evidence to support the implementation of a dynamic allocation strategy with allocation decisions based on capital flow movements. In out of sample testing, the dynamic strategy was shown to improve diversification and preservation of capital for a developed markets portfolio in the form of improved returns, Sharpe ratios and lower volatility for some of the predicted downturns. Improvements could be made to the systematic process for deciding allocation changes (e.g. a different threshold for determining capital flow surges or an allocation reduction relative to a country's level of capital flows) in order to possibly enrich the results. Further research with more extensive data is warranted to better evaluate the effects for emerging markets.

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Appendix A: Process for allocation decisions from the literature

Ang and Bekaert (2002) Consider a U.S. Investor looking to maximize end of period utility through a monthly rebalancing of a portfolio of equities and risk-free assets. Solve for the optimal portfolio weights for each month, maximizing the constant relative risk aversion utility. Optimization accounts for the regime in the current month and the transition probabilities to other regimes.
Ang and Bekaert (2004) Use mean-variance optimization, rebalanced monthly to determine portfolio weights. Inputs for optimization problem are dependent on the on regime at the given time.
Das and Uppal (2004) – Systemic Risk and International Portfolio Choice Determine an investor's optimal portfolio weights based on their jump diffusion model of returns. A stochastic dynamic program is used to determine the pricing of the assets. The perspective of a U.S. investor seeking to maximize the expected utility at terminal wealth is considered. Find the weights for a risk-free asset, U.S. equities and foreign equities that maximize terminal wealth for three different levels of risk aversion.
Hauptmann et al. (2014) Considers a stock bond portfolio composed of a risk-free asset and U.S equities. Employ rules-based allocation decisions for two different strategies. For strategy A, when the model predicts a bad regime for a given month, invest in the risk-free asset, otherwise invest in the S&P 500 index. For Strategy B, if a month is predicted to be in a calm regime, the probability of being in the calm regime serves as the allocation to the S&P 500 index. If the month is expected to be in a turbulent regime, the probability of being in the negative turbulent regime (having mainly negative returns) is the allocation weight for the risk-free asset (the turbulent regime is split into turbulent positive and turbulent negative).

Kritzman, Page and Turkington (2012) Considers a portfolio through the lens of risk premiums. Given an initial exposure to the risk premiums, the investor implements “defensive tilts” for the months when an event regime is predicted. The tilts reflect reduced allocation to certain risk premiums or addition allocation to defensive trades. Different tilts are employed, depending on the type of even regime predicted. The values assigned to the defensive tilts are arbitrary and used for illustrative purposes. Table 2 for the tilts.
Solnik and Watewai (2016) Consider a U.S. investor with constant relative risk aversion, seeking to maximize terminal wealth. Solve for the optimal portfolio weights across regional equities and a risk-free asset. At a given time, the investor has knowledge of previous asset returns and wealth, but not of regimes. The likelihood of a regime is dependent on the historical returns and included in the optimization problem.

Appendix B: Baum-Welch Algorithm Initial Parameter Values

I assume the initial probability of being in regime 1 is 0.5, which means that the initial probability of being in regime 2 is also 0.5. The probability of observing the data while in regime 1 is assumed to follow the probability density function of the Normal distribution[13] with mean and standard deviation equal to the mean and standard deviation of the CLI data. The probability of observing the data while in regime 2 assumes a Normal distribution with a higher mean, equal to the average of the CLI data plus 1.5 standard deviations (where the standard deviation is that of the CLI data). The transmission matrix assumptions are a 0.8 probability of remaining in the same regime and a 0.2 probability of switching.

[13] The probability density function for a normally distributed variable X with mean μ and variance σ^2 is

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/(2\sigma^2)}$$

Appendix C: Data and Results

Table 1: List of countries included in the portfolio

The countries included in the developed market and emerging market portfolios are those in the MSCI World and MSCI Emerging Market indices with at least a 20-year history (December 2018 to December 1998) of capital flow data. Source refers to the source of the capital flow data.

Developed Countries	
MSCI World Countries	Source
Australia	OECD
Austria	IMF
Canada	OECD
Denmark	OECD
Finland	OECD
France	OECD
Germany	OECD
Italy	OECD
Japan	OECD
Netherlands	OECD
New Zealand	IMF
Norway	OECD
Portugal	OECD
Spain	OECD
Sweden	OECD
United Kingdom	OECD
United States	OECD

Emerging Markets	
MSCI EM Countries	Source
Brazil	OECD
China	OECD
Czech Republic	OECD
Greece	IMF
Hungary	IMF
Korea	IMF
Mexico	IMF/Datastream
Peru	IMF
Philippines	IMF
Russia	IMF
South Africa	OECD

Table 2: In sample regime switching model parameters

The in-sample parameter estimates and their standard errors for the regime switching model. The mean and standard deviation are the mean and standard deviation of the CLI for the specified regime. Persistence refers to the probability of remaining in the same regime. The beginning in-sample period for global CLI estimates is from November 1973 to December 1997. The beginning in-sample period for the U.S. CLI based estimates is from January 1955 to December 1997. The parameter estimates are obtained using the Baum-Welch algorithm. The standard errors are calculated from the covariance matrix as derived from the information matrix of the log-likelihood function.

	GLOBAL CLI REGIMES		**U.S. CLI REGIMES**	
	Regime 1 (normal)	Regime 2 (downturn)	Regime 1 (normal)	Regime 2 (downturn)
MEAN	100.7	99.3	100.8	98.5
STANDARD ERROR	0.02	0.06	0.04	0.08
STANDARD DEVIATION	0.40	0.83	0.82	1.00
STANDARD ERROR	0.00	0.03	0.01	0.02
PERSISTENCE	0.96	0.95	0.97	0.93
STANDARD ERROR	0.03	0.03	0.02	0.02

Table 3: Out of sample predicted downturn regimes from global CLI

The start, end and duration of the downturns predicted from the regime switching model based on global CLI are presented in this table along with annualized returns for the MSCI World and MSCI EM indices for the respective periods. A downturn starts in the month when the probability of being in the downturn regime is greater than 60% and ends when the probability of being in the downturn regime moves below 60%.

Predicted Downturn	**Start**	**End**	**Duration**	**MSCI World Return**	**MSCI EM Return**
Downturn 1	May-98	Jul-99	15 months	12.64%	19.79%
Downturn 2	Mar-01	Jan-04	35 months	0.24%	15.58%
Downturn 3	Aug-08	Feb-10	19 months	-6.92%	3.54%
Downturn 4	May-12	Sep-13	17 months	24.31%	9.78%
Downturn 5	Mar-16	Dec-16	10 months	10.60%	10.47%

Table 4: Out of sample predicted downturn regimes from U.S. CLI

The start, end and duration of the downturns predicted from the regime switching model based on the U.S. CLI are presented in this table, along with the annualized returns for the MSCI World and MSCI EM indices for the respective periods. A downturn starts in the month when the probability of being in the downturn regime is greater than 60% and ends when the probability of being in the downturn regime moves below 60%

Predicted Downturn	**Start**	**End**	**Duration**	**MSCI World Return**	**MSCI EM Return**
Downturn A	Feb-01	Dec-03	35 months	-2.65%	9.70%
Downturn B	Oct-08	Jan-11	28 months	15.94%	32.89%
Downturn C	Oct-11	Apr-12	7 months	-5.52%	-14.87%
Downturn D	Feb-16	Jul-17	18 months	17.07%	29.24%

Table 5: Countries to be underweighted (global CLI downturns)

The countries underweighted during the downturns predicted from global CLI are reported in this table. A country is underweighted if there is a surge in its capital flows at the start of the downturn. A surge is defined as a year over year difference in capital flows that is more than one standard deviation above its 5-year historical average difference.

Downturn 1 Jun 1998 - Jun 1999	Downturn 2 Mar 2001 - Jan 2004	Downturn 3 Aug 2008 - Feb 2010	Downturn 4 Jun 2012 - Sept 2013	Downturn 5 Mar 2016 - Jan 2017
Developed Market Countries				
Netherlands	Germany	Spain	Italy	Italy
	Netherlands		Japan	United Kingdom
	United States			
Emerging Market Countries				
	Russia	Czech Republic		Brazil
				Russia

Table 6: Countries to be underweighted (U.S. CLI downturns)

The countries underweighted during the downturns predicted from U.S. CLI are reported in this table. A country is underweighted if there is a surge in its capital flows at the start of the downturn. A surge is defined as a year over year difference in capital flows that is more than one standard deviation above its 5-year historical average difference.

Downturn A Feb 2001 - Dec 2003	Downturn B Oct 2008 - Jan 2011	Downturn C Oct 2011 - Apr 2012	Downturn D Feb 2016 - Jul 2017
Developed Market Countries			
Germany	Canada	Canada	Italy
Netherlands	Netherlands	Denmark	United Kingdom
United States		Japan	
Emerging Market Countries			
Russia	Russia		Brazil
			Russia

Table 7: Risk and return results for the static and dynamic portfolios (global predicted downturns)

Annualised returns, standard deviations, Sharpe ratios and Maximum drawdowns based on monthly data in USD are reported in this table. Results are presented with a one-month lag relative to the downturn period (as estimated by the global CLI) in order to account for implementation of the weight changes. Returns are calculated from the monthly data for market capitalizations and returns from the MSCI country indexes. The Sharpe ratio is based on the U.S. risk free rate. The Maximum drawdown measures the worst peak to trough loss incurred before returning to a new peak.

	Developed Markets Portfolio								Emerging Markets Portfolio							
	Return		Standard Dev		Sharpe		Max Drawdown		Return		Standard Dev		Sharpe		Max Drawdown	
	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic
Full Period																
Jan 1998 - Dec 2018	4.13%	4.41%	15.17%	15.07%	0.22	0.24	-54.69%	-54.70%	4.88%	4.64%	24.91%	24.91%	0.25	0.24	-65.00%	-64.95%
Downturn 1																
May 1998 - Jul 1999	14.62%	14.94%	18.11%	18.18%	0.60	0.61	-13.72%	-13.75%	22.87%	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Downturn 2																
Mar 2001 - Jan 2004	0.86%	2.56%	16.91%	16.30%	0.03	0.13	-34.82%	-33.19%	18.58%	17.56%	22.24%	22.36%	0.81	0.76	-25.25%	-25.39%
Downturn 3																
Aug 2008 - Feb 2010	-6.10%	-6.10%	27.86%	27.77%	-0.10	-0.10	-43.81%	-43.82%	1.26%	1.41%	40.93%	40.94%	0.23	0.24	-49.94%	-49.86%
Downturn 4																
May 2012 - Sept 2013	24.64%	24.57%	8.58%	8.67%	2.62	2.59	-2.54%	-2.75%	9.99%	9.99%	12.98%	12.98%	0.79	0.79	-15.33%	-15.33%
Downturn 5																
Mar 2016 - Dec 2016	11.51%	12.12%	6.26%	6.12%	1.72	1.85	-1.82%	-1.68%	13.91%	10.59%	12.48%	11.82%	1.08	0.88	-4.95%	-5.77%

Table 8: Risk and return results for the static and dynamic portfolios (U.S. CLI predicted downturns)

Annualised return, standard deviation, Sharpe ratio and Maximum drawdown based on monthly data in USD are reported in this table. Results presented with a one-month lag relative to the downturn period (as estimated by U.S. CLI) in order to account for implementation of the weight changes. Returns are calculated from the monthly data for market capitalizations and returns from the MSCI country indexes. The Sharpe ratio is based on the U.S. risk free rate. The Maximum drawdown measures the worst peak to trough loss incurred before returning to a new peak.

	Developed Markets Portfolio								Emerging Markets Portfolio							
	Return		Standard Dev		Sharpe		Max Drawdown		Return		Standard Dev		Sharpe		Max Drawdown	
	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic
Full Period																
Jan 1998 - Dec 2018	4.13%	4.38%	15.17%	15.05%	0.22	0.24	-54.69%	-54.74%	4.88%	4.68%	24.91%	24.86%	0.25	0.24	-65.00%	-64.39%
Downturn A																
Feb 2001 - Dec 2003	-1.97%	-0.40%	17.33%	16.68%	-0.13	-0.05	-34.82%	-33.19%	12.15%	11.15%	23.35%	23.50%	0.53	0.49	-25.30%	-25.90%
Downturn B																
Oct 2008 - Jan 2011	16.95%	16.53%	20.82%	20.75%	0.85	0.84	-21.36%	-21.44%	31.92%	31.88%	25.99%	25.69%	1.19	1.20	-13.84%	-14.59%
Downturn C																
Oct 2011 - Apr 2012	-4.43%	-3.53%	16.22%	16.11%	-0.21	-0.16	-9.94%	-9.79%	-16.13%	-16.13%	27.41%	27.41%	-0.52	-0.52	-17.45%	-17.45%
Downturn D																
Feb 2016 - Jul 2017	17.71%	18.14%	6.79%	6.75%	2.37	2.44	-1.82%	-1.68%	33.72%	32.52%	14.81%	14.14%	2.02	2.04	-4.95%	-5.77%

Table 9: Statistical significance for differences in returns, variances and Sharpe ratios for the static and dynamic portfolios (global predicted downturns)

This table reports the p-values for two sample tests of differences in mean returns (z-test) and for two sample tests of differences in variances (F-test). The type I error level (**α**) required for the difference in Sharpe ratios to be significant is presented in the final column. This **α** is estimated using the Jobson-Korkie test for equal Sharpe ratios. * indicates significance at the 10% level.

	Developed Markets Portfolio			Emerging Markets Portfolio		
	Difference in Return P-Value	Difference in Variance P-Value	Difference in Sharpe α level for significance	Difference in Return P-Value	Difference in Variance P-Value	Difference in Sharpe α level for significance
Full Period	0.9569	0.9173	0.3124	0.9763	0.9984	*0.0818
Downturn 1	0.9898	0.9889	0.2846	n/a	n/a	n/a
Downturn 2	0.9088	0.8300	0.3954	0.9631	0.9763	0.1388
Downturn 3	0.9995	0.9891	0.8650	0.9974	0.9994	0.1310
Downturn 4	0.9956	0.9674	0.6672	n/a	n/a	n/a
Downturn 5	0.9553	0.9476	*0.0512	0.8709	0.8732	0.3078

Table 10: Statistical significance for differences in returns, variances and Sharpe ratios for the static and dynamic portfolios (U.S. predicted downturns)

This table reports the p-values for two sample tests of differences in mean returns (z-test) and for two sample tests of differences in variances (F-test). The type I error level (**α**) required for the difference in Sharpe ratios to be significant is presented in the final column. This **α** is estimated using the Jobson-Korkie test for equal Sharpe ratios. ** indicates significance at the 5% level.

	Developed Markets Portfolio			Emerging Markets Portfolio		
	Difference in Return P-Value	Difference in Variance P-Value	Difference in Sharpe α level for significance	Difference in Return P-Value	Difference in Variance P-Value	Difference in Sharpe α level for significance
Full Period	0.9631	0.8984	0.3628	0.9789	0.9745	0.3078
Downturn A	0.9163	0.8244	0.4532	0.9642	0.9713	0.1336
Downturn B	0.9845	0.9864	0.2502	0.9968	0.9521	0.7872
Downturn C	0.9753	0.9867	**0.0358	n/a	n/a	n/a
Downturn D	0.9624	0.9812	0.1286	0.9522	0.8497	0.8414

Figure 1: Out of sample global CLI predicted downturns vs. actual global CLI turning points

This figure compares the out of sample downturn predictions obtained from the regime switching model with global CLI to the actual turning points of the global CLI as obtained from the OECD.

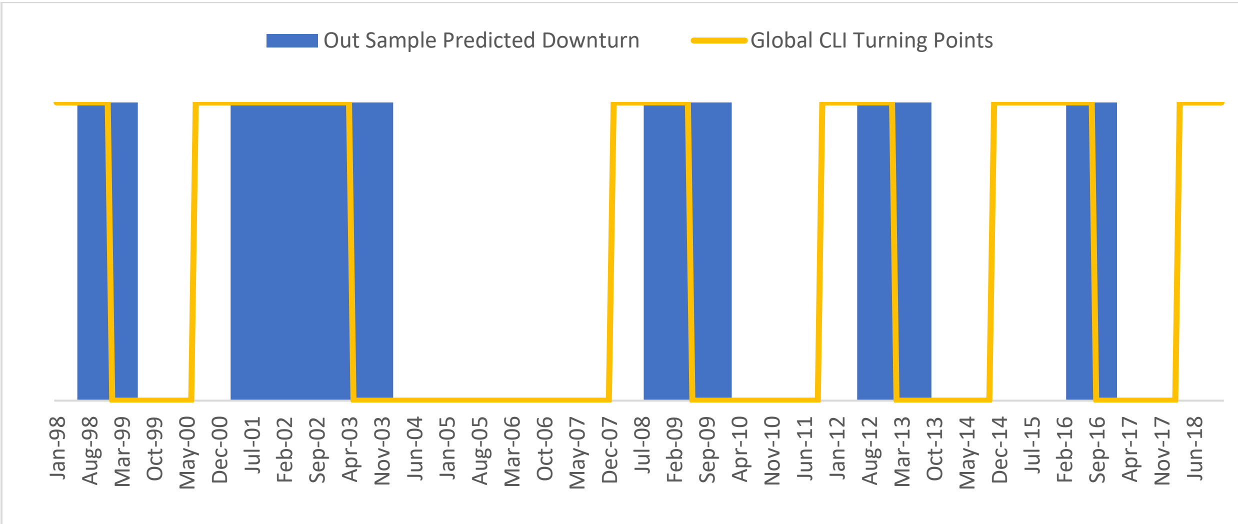

Figure 2: Out of sample U.S. CLI predicted downturns vs. actual U.S. CLI turning points

This figure compares the out of sample downturn predictions obtained from the regime switching model with U.S. CLI to the actual turning points of the U.S. CLI as obtained from the OECD.

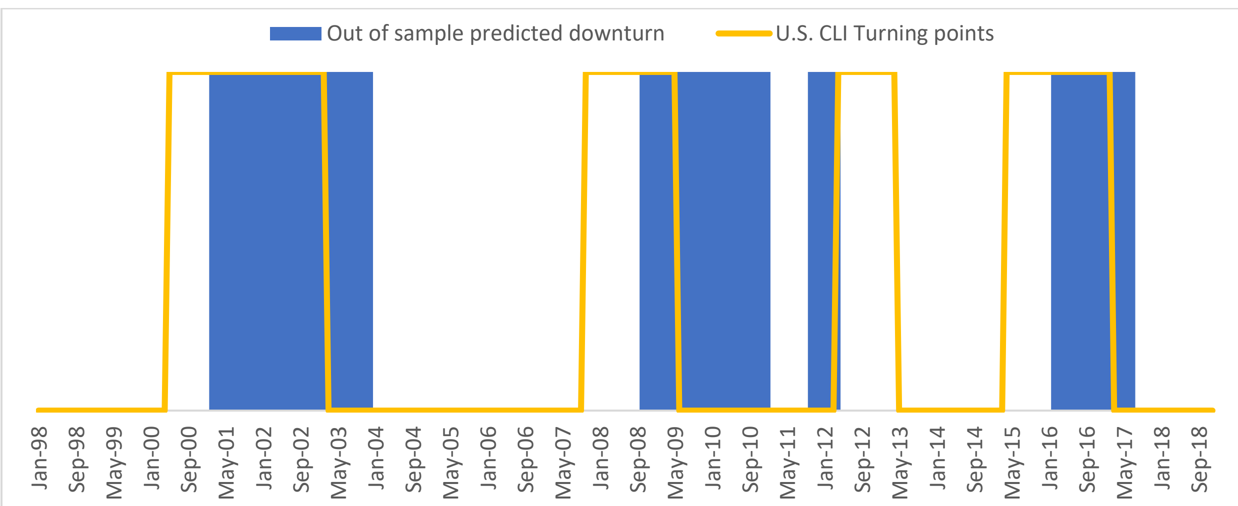

Figure 3: In sample global CLI predicted downturns vs. actual global CLI turning points
This figure compares the in sample downturn predictions obtained from the regime switching model with global CLI to the actual turning points of the global CLI as obtained from the OECD.

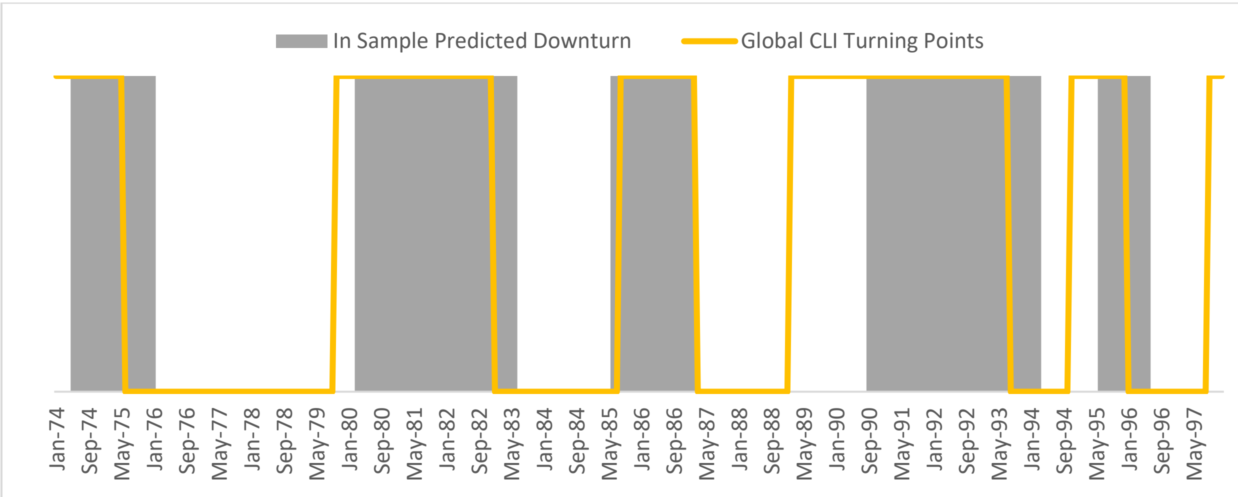

Figure 4: In sample U.S. CLI predicted downturns vs. actual U.S. CLI turning points
This figure compares the in sample downturn predictions obtained from the regime switching model with global CLI to the actual turning points of the global CLI as obtained from the OECD.