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An empirical analysis

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Macro-based Asset Allocation: An empirical analysis[1]

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Abstract

Macro-based asset allocation, i.e., the identification of turning points in macro-financial cycles and the allocation of assets accordingly, has attracted a lot of interest in recent years. This interest was sparked by volatile financial markets, more synchronized returns across asset classes and countries as well as the low interest rate environment. A horse-race among different asset allocation strategies suggests that macro-based asset allocation informed by trends in continuous indicators characterizing the business and financial cycle could be a promising alternative for medium- and long-term investment. Despite changes in the relationship between macro-financial cycles and asset price cycles during the last three decades, the most promising specifications did roughly anticipate turning points in asset price cycles, resulting in favorable returns and low portfolio volatility. The authors appreciate the promising role of this approach, but urge caution given the complexity of the inherent interactions.

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Contents

Figures

Tables

I. Introduction

There are a number of reasons for the growing importance of risk-based medium- and long-term investment. One is the fact that the assets under professional management have seen a steady growth during the past two decades, an important driver being savings for retirement in advanced economies (e.g., IMF 2011a). More importantly, during the great financial crisis (GFC), all asset classes but cash and gold experienced severe market falls at the same time and the traditional, Markowitz-based type approach based on statistical properties has been unable to shield investors from losses.

More generally, asset price cycles have become more volatile and synchronized across asset classes, sectors and jurisdictions (see Rey (2015); BIS (2017a); IMF (2017); Claessens and Kose (2017a) and Jorda et al. (2018)), reinforcing the case for a good timing of investments.[3] This trend has featured since the late 1980s and mirrors macro-financial conditions: real economic integration (i.e. through trade) and financial liberalization have resulted in more synchronized business[4] and financial cycles[5], along with higher amplitudes of financial cycles[6], which culminated in the GFC. Financial integration has been more dynamic than real economic integration, i.e., international capital flows (see IMF (2016) for an overview) have increased more rapidly than cross-border trade – characterized by the rise of investors actively managing their balance sheet positions in international markets (e.g., Haldane 2014, BIS 2017b, Claessens and Kose, 2017a), including savings for retirement in advanced economies (e.g., IMF 2011a).

As a result, a number of risk-based investment strategies have emerged[7], which account for the (macro-financial) context. Among these concepts, we focus on *macro-based asset allocation,* a concept that is related to global macro or global tactical asset allocation but with a medium- to long-term focus (see Kollár (2013), for example). Its defining element is to exploit the fact that asset prices are ultimately driven by macroeconomic fundamentals, suggesting that taking the macroeconomic cycle[8] into consideration (by re-allocating asset classes accordingly) produces higher returns and lower portfolio volatility than classical approaches to asset allocation – the mean-variance approach by Markowitz (1952) and the model by Black and Litterman (1992), but also related concepts based on

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3 E.g., Financial Times, "Time to study cycle turning points", June 12, 2011.

4 Business cycles have been highly synchronized across countries during the past 40 years (Claessens and Kose, 2017b). During that period, synchronized recessions in advanced economies occurred four times (during the mid-1970s, the early 1980s, the early 1990s and 2008/9).

5 See Jorda et al. (2018), for example.

6 The BIS (2017b , p. 110), for example, notes that it "it is no coincidence that (…) there were few [financial crises] (...) in the era of financial repression which lasted into the 1970s."

7 The (i) risk-factor based allocation; (ii) macroeconomic allocation (or macro-based asset allocation); (iii) thematic allocation; and (iv) tactical implementation of asset allocation (World Economic Forum, 2011).

8 We refer to the macroeconomic cycle as a general notion, and distinguish, where relevant, between the business cycle and the financial cycle.

risk factors and smart-beta strategies applied in recent years) – at least over the medium- to long-term.

The basic idea is anything but new: Keynes acknowledged that "investment results largely depend on how one behaves near the top and near the bottom" [of the market cycle].

We run a horse-race comparing the usefulness of continuous macro-financial cycle indicators with alternative approaches applied by investors, including traditional asset allocation and other macro-based asset allocation approaches used by institutional investors. Our key innovation is that we build upon concepts used for early warning analysis of financial stability (e.g. Borio (2009, 2012), Borio et al. (2014), Shin (2013) and Stremmel (2015)[9]) to inform asset allocation.

Operationalizing macro-based asset allocation is challenging, though: first, the concept requires anticipation of turning points in business and financial cycles so as to re-balance portfolios at "the right time" (*timing*); second, a central question is whether there is a re-occurring "optimal" allocation of assets at different stages of the cycle (*asset allocation conditional on the cycle*). As the timing of investments will never be ideal (also given other confounding factors such as monetary policy and regulation), the study will reveal whether it is also worth following macro-based strategies if one gets it "roughly right" and what to expect if "things go wrong".[10]

We follow two principles: first, keep things simple – e.g., by relying on observable macro-financial trends, recognizing the subordinate track record of macroeconomic forecasting (e.g. An et al., 2018)[11]. Second, we seek to generalize our findings, drawing upon an applied example rather than optimize the performance of specific strategies.

Our contribution is two-fold:

- First, we analyze the usefulness of macro-based asset allocation as a newly emerging investment concept for medium- to long-term investment. To this end, we study the relative importance of different determinants for performance, most importantly the choice of the cycle indicator as well as operational aspects (e.g. the availability of data for real time analysis and the role of transaction costs).
- Second, we contribute to the literature that links asset prices to macroeconomic fundamentals, a key concern for various purposes (e.g., for financial stability);

Studying performance under real-time out-of-sample conditions we found that the use of a multivariate financial cycle indicator outperformed all other specifications, particularly for the United States, but also for Germany, the United Kingdom and Japan (*Figure 3*).

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9 See also Aikman et al. (2014), Alessi et al (2014), Behn et al. (2013), Claessens et al. (2012), Drehmann et al. (2012), ECB (2014), IMF (2011b). Adding additional variables, such as microeconomic indicators, was found to further enhance these indicators in terms of their early warning properties, but adds complexity.

10 Raffinot (2017), for example, suggests that "macroeconomists can get rich (…) nowcasting output gap turning points", but the jury is still out.

11 See also FT ("IMF shows poor track record at forecasting recessions", as of April 9, 2018).

Sensitivity analyses suggest that the choice of "false" specifications will negatively affect performance, but does not lead to highly inferior performance. The outcome for Japan documents that the concept can also be useful in a macro-financial environment characterized by stagnating equity prices and low yields for fixed income securities.

In line with previous studies, we find that during upswings of the macro-financial indicators, high yielding asset classes (equities and real estate, as well as, to a lesser degree, high-yield corporates) perform best, while safe assets (sovereign bonds, cash, investment grade corporates) and countercyclical asset classes (commodities, gold) dominate during contraction periods.

The main determinant for strong performance is the choice of the macro-financial cycle indicator, namely its signaling properties for turning points in asset price cycles (found to be higher for multivariate indicators), but also other inherent properties, such as the level of volatility of the signaling indicators, which is found to negatively affect performance. Other factors, such as operational aspects (e.g. the timeliness of the availability of the indicators) and the choice of the "optimal" asset allocation conditional on the state of the signaling indicator are found to be of secondary importance. The latter reflects the fact that macro-based asset allocation will, by definition, be geared towards greater portfolio concentration, exploiting upside opportunities when they occur, while avoiding losses during other times (see *Appendix 2* for further illustration).

The time period covered in this study includes less than three full asset price cycles, which warrants caveats in terms of generalization.[12] Future refinements to the concept (e.g. to improve the identification of turning points in asset price cycles in real time) will remain an important element to enhance performance and robustness.

The rest of the paper is structured as follows: Section II presents a stylized theoretical framework. Macro-based approaches to portfolio management are outlined in section III. The empirical part includes a description of data (section IV) followed by an applied example (section V). Section VI concludes.

II. Stylized theoretical framework of the interaction between the macroeconomic conditions and asset prices

Asset classes behave differently in varying macroeconomic environments, i.e., it is well known that there is no single asset class that outperforms at all times (e.g. Ilmanen (2011), Sheikh and Sun (2011)). This is because financial markets by their very nature generally reflect the current and expected developments in the economy, the *fundamentals.* They are more volatile, though, than fundamentals would imply (and thus sometimes deviate substantially from predicted values based on fundamentals, see, e.g., Claessens and Kose,

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[12] We sought to avoid over-calibration, which will likely improve the underlying forward-looking properties.

2017a). Nevertheless, the asset returns of different asset classes[13] (equities, bonds, commodities, real estate, etc.) react in one way or another to economic growth, inflation, credit growth, etc., at least in the medium-term. Claessens and Kose (2017a), for example, document correlations between te year-over-year growth rates of asset prices and output between 0.3 and 0.4 for a sample of 18 advanced economies during 1970 till today, and that those correlations have increased in recent decades.[14]

The relationship between macroeconomic conditions and asset price cycles is two-sided: macroeconomic developments (including those in the financial sector) have an impact on investors' decision making, which in turn influence flows to individual asset classes and thereby asset prices.[15] There are a number of studies documenting the link between credit conditions and asset prices, suggesting that strong credit growth in the US was associated with elevated levels of corporate profit, such as in the post-gold standard era of the 1970s, during the dot.com bubble in the late 1990s, and the housing boom after 2001.[16] We also acknowledge empirical evidence suggesting that asset prices anticipate future earnings' growth and other fundamentals (although investors will have different expectations and beliefs). Similarly, asset prices will have at least some effect on output (as a "financial accelerator"). In this study explore whether business and financial cycle indicators signal changes in asset price trends sufficiently early on to re-balance investments.[17]

[13] The link between the macro economy and the asset class behavior differs - e.g. the value of equities (ownership stakes in companies) is determined by companies' expected future earnings, which in turn reflects the expected growth of the economy; while bond prices are driven by expectations on economic growth and inflation rates. However, in general, the value of any asset is the discounted present value of its future cash flow streams, which are strongly driven by macroeconomic developments (although there are also other factors at play).

[14] We also recognize that returns of individual securities reflect their specific characteristics, but do not study such levels of granularity. For example, we do not look at sectoral equity indices, which are a dimension to consider for investors.

[15] We recognize that the precise nature and direction of causality is unclear. We acknowledge empirical evidence that suggests that asset prices anticipate future earnings' growth and other fundamentals, i.e. their signaling role (although investors will have different expectations and beliefs). At the same time, asset prices will have at least some effect on output (as a "financial accelerator"). Ultimately, in the study herein we use business and financial cycle indicators that are meant to signal changes in asset prices sufficiently early on to re-balance investments. For a broader discussion on the two-way interaction between real economy and the financial sectors (supply side: importance of balance sheets of financial institutions on real economic activity; demand side: how do changes in borrowers' balance sheets amplify macroeconomic fluctuations – the literature on "financial accelerators") see, for example, Claessens and Kose (2017a) and Claessens and Kose (2017b).

[16] For the link between (banks') lending conditions and equity prices see Chava et al. (2010), Ilmanen, (2011) and for the impact of credit growth more generally see Bordo et al. (2001), Reinhart and Rogoff (2008), Mendoza and Terrones (2008), Borio and Drehman (2009), Ng (2011), and De Nicolo and Lucchetta (2010).

[17] For a broader discussion on the two-way interaction between real economy and the financial sectors (supply side: importance of balance sheets of financial institutions on real economic activity; demand side: how do changes in borrowers' balance sheets amplify macroeconomic fluctuations – the literature on "financial accelerators") see, for example, Claessens and Kose (2017a) and Claessens and Kose (2017b).

From an investor's perspective, asset allocation activities are meant to be forward-looking but investors' behavior is not uniform and synchronized: Some investors, those studying the dynamics of financial markets and their interaction with the economy, are likely to be the first ones to anticipate changes in the macroeconomic environment and react upon it.[18] The asset price movements driven by those investors will attract others. The herds of investors will thus move from underperforming assets to other asset classes, and momentum takes over.[19]

The market mechanics are, however, more complex than that. The expectations of investors about future economic developments and linking those expectations to the valuation of financial assets are subjective, based on imperfect knowledge and subject to interpretation of the observed information. Therefore, expectations will differ from one investor to another and investors' ignorance and imperfect knowledge manifests itself in the diversity of expectations (e.g. Kurz (1994), Brock (2007)).[20] Furthermore, investors' expectations can be "wrong" and these misperceptions will be revealed with new economic data becoming available, which in turn creates investment opportunities for those who first realize that the prevailing expectations were untenable, as documented in Carlin et al (2014), for example.[21]

Investors are usually aware of the long-run averages of asset class' returns and their link to fundamentals.[22] However, they hold different beliefs, interpretations and forecasts of short-term returns, e.g., how current and expected events translate into the prices of financial assets. In fact, the GFC has pushed back the efficient market hypothesis, at least for short-term price developments, a theory which had dominated other strands of economic theory before the crisis (e.g. Claessens and Kose, 2017a).

As said, investors' expectations are often correlated, leading to self-reinforcing herding behavior of euphoria and anxiety, characterized by over- and undershooting markets. This market feature is particularly relevant for markets with a pure trading purpose (rather than a commercial one) and is amplified by leverage. When a sizeable group of investors realizes that their expectations with respect to the direction of market prices have been

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[18] As discussed by Timmer (2016), for example, institutional investors do not behave uniformly, though. Studying asset allocation of debt securities by financial institutions, he finds banks and investment funds to react pro-cyclically to price changes, while insurance firms and pension funds are found to follow countercyclical behavior.

[19] See Vayanos and Woolley (2013) on the effect of the Principal-Agent problems in the asset management industry on value and momentum phenomena, and Asness et al. (2013) on the empirical evidence of the presence of value and momentum across all major asset classes.

[20] On the theory of rational beliefs see Kurz (1994), and on its use in explaining financial markets behavior see Brock (2007).

[21] Carlin et al. (2014) document the effect of differences of investors' opinion on asset prices.

[22] This is what valuation-based long-term investment seeks to exploit, along with other relevant factors such as the risk appetite, economic environment and monetary policy etc. Evidence suggests that the 10–year earnings yield (the inverse of the price-to-earnings ratio) of US companies in the S&P 500 Index is highly correlated with the timing of an investment over ten years (using data from 1970), but there is hardly any correlation if one looks at the next month only.

false, they re-evaluate their expectations and adjust their portfolio holdings. In a downturn, this usually leads to significant downward adjustments in asset prices and to increased market volatility.[23] The distribution of expectations and beliefs therefore affects asset prices.[24]

Correlated expectations can build up over a short period until they are being re-evaluated, or over an extended period of time, the latter leading to longer boom and bust cycles. The longer the build-up of investors' actions based on false expectations, the more abrupt and costlier the eventual unfolding market correction, can be sometimes fueled a process of self-fulfilling expectations.[25]

III. Concept of macro-based approach to asset allocation

The traditional Markowitz (1952) and Sharpe (1964) approach to strategic asset allocation is static, long-term embedded, benchmark-based and business cycle neutral. It assumes a world with a single risk factor, constant expected returns over time, investors caring only about the means and variances of asset returns, frictionless and efficient markets and rational investors. The GFC has challenged at least some of these assumptions.

The emerging consensus in the literature assumes a more complex world with multiple risk factors, time-varying risk premia, skewness in returns and liquidity preferences, supply and demand effects on asset prices and various market inefficiencies, behavioral biases, irrational investors and market frictions (see Ilmanen, 2011). Accordingly, the World Economic Forum (2011) distinguishes four emerging risk-based concepts to asset allocation: (i) risk-factor based allocation; (ii) macroeconomic allocation (or macro-based asset allocation); (iii) thematic allocation; and (iv) tactical implementation of asset allocation. All of those strategies account, at least to some degree, for the (macro-financial) context rather than relying "only" on (reduced-form) statistical properties.

Risk-factor based allocation and smart-beta strategies rely on risk factors (i.e., the risk and return characteristics of investments, such as market capitalization/size, income, growth,

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[23] As shown by Kurz (1994), the theory of rational beliefs can better explain the observed market volatility than traditional models based on rational expectations and efficient markets. A significant part of market volatility comes from investors' re-evaluating their beliefs once they turn out to be wrong by new data. Shiller (1981) showed that traditional models of equity market valuation explain only one fourth of observed volatility in equity markets and do not necessarily explain the observed equity risk premium.

[24] Investors are also trying to forecasts the forecasts of other investors, but since no one possesses a perfect forecast, subsequent realization of false forecasts by some investors creates additional market volatility. See also Keynes (1936) on the related concept of "beauty contest".

[25] Or, as Padoa-Schioppa (2010) puts it: "[there is a] commerce-driven and speculation-driven [element to financial] transactions [which] are hard to separate because an element of speculation (choosing the best moment to buy or sell) is present in both. (…) Without a component of speculation-driven transactions financial markets would probably not be sufficiently deep or liquid to perform their allocation function efficiently. However, if this component grows too large, markets may become more unstable." See also Borio (2012) and Turner (2015) on financial cycles and the build-up of imbalances.

real value, inflation-linkage, volatility and liquidity) rather than directly on asset classes.[26] This is because risk factors were found to be less correlated than asset class returns, especially during periods of market turbulence (and thus yielding higher diversification benefits – see Bender et al (2010), for example), but ultimately such relationships face the criticism of in-sample bias, i.e. might only hold temporarily. More generally, the approach remains closely linked to the traditional asset allocation approach (and asset allocation remains broadly similar) in that investors rely on micro characteristics to determine optimal portfolios to inform or complement *strategic asset allocation* (with performance being compared to an appropriate benchmark).[27]

A commonly used approach to macro-based asset allocation uses four "inflation-growth" quadrants, depending on whether inflation and growth are higher or lower than average or median levels observed in the past (or than expected). By definition, the likelihood of each "inflation/economic growth" regime's occurrence is approximately the same over a longer period of time, unless the level of growth and/or inflation changes substantially. As for all macro-based asset allocation strategies, the fundamental principle is that the performance of asset classes in different macroeconomic regimes will offset each other and the investor will remain with reaping the long-term risk premium of each asset class.[28] We use this approach, referred to as *growth-inflation regime*, as a key benchmark (see *Table 1*).

While there is a growing community of investors who apply business cycle analysis to enhance medium- and long-term asset allocation (e.g. to inform tactical asset allocation decisions) but also for short-term investments – see de Longis and Hamilton (2015), for example[29], less focus has been placed on financial cycles.

In this study, we develop a framework to use continuous indicators (henceforth also *signaling indicators*) characterizing the business *and* financial cycle (see *Table 1*) for asset allocation purposes, which is benchmarked against other common investment strategies. A stylized graph of our approach is shown below.

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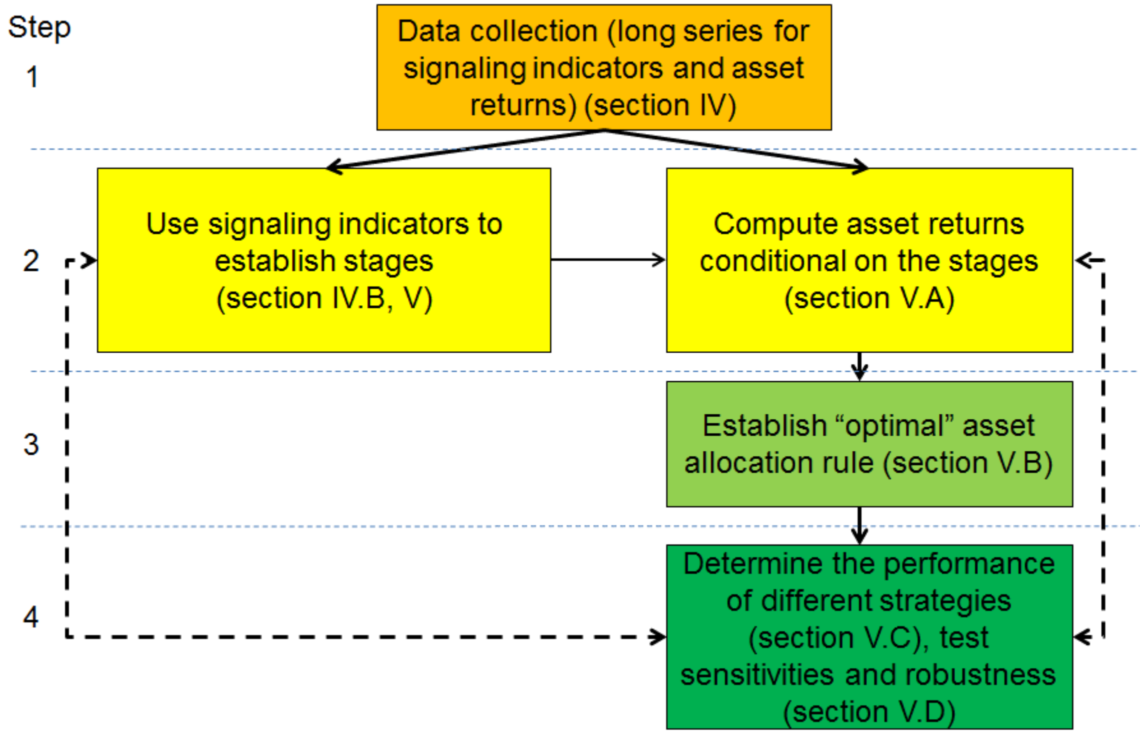
26 See, for example, Credit Suisse (2018), which documents that researchers have identified more than 300 factors. One such study is Franz (2018).

27 For related studies documenting the use of the macro-based asset allocation among practitioners (hedge funds and institutional investors) see Bhansali (2007), Brooks et al. (2014), Donay (2015), Ilmanen (2011), Jakobson and Nuttall (2011), O'Neill et al. (2011), Oppenheimer et al. (2009a, 2009b), Page et al. (2010), Raol (2017), and Sheikh and Sun (2011).

28 A variant of this approach is the risk parity approach. In this case, the weight of each asset class is volatility-adjusted so that each quadrant contributes the same amount of volatility to the total portfolio. On the risk parity approach from a practitioners' perspective see Dalio (2011), Dalio et al. (2015), Hurst et al. (2010), and Mendelson et al. (2011), for example.

29 In their study, they construct leading business cycle indicators based on business and consumer surveys, manufacturing and construction/housing activity as well as monetary and financial conditions. Other multivariate business cycle indicators used to signal turning points include the *Bull/Bear market indicator* by Goldman Sachs, for example, which is based on five factors, namely growth momentum of the Institute for Supply Management (ISM) manufacturing index, inflation, unemployment, valuation and the yield curve, or Citibanks *Panic/Euphoria model*, which focuses on investor sentiment (based on metrics such as margin debt, options trading and newsletter sentiment).

Figure 1. Stylized graph of adopted approach to macro-based asset allocation



Source: Authors

After collecting relevant data (step 1), one first establishes the stages of the cycle using different signaling indicators (step 2a). Next, we identify the behavior of asset class returns during those business and financial cycle stages observed in the past (step 2b).[30] The asset allocation rules (step 3) account for the risk aversion of the investors (by choosing more or less concentrated portfolios, see section V). In the final step (step 4), we compare the performance of the different strategies, as well as their sensitivities vis-à-vis underlying determinants and robustness. Key elements of the framework are outlined below, supplemented by the technical appendix (*Appendix 1*).

IV. Data

A. Asset classes

We consider eight asset classes for Germany, Japan the United Kingdom and the United States, subject to their availability (see *Appendix 1*): cash, government bonds, investment

[30] As such, we assume that investors are able to map the average behavior of asset classes in different macroeconomic regimes despite the noise caused by market volatility.

grade and high yield corporate bonds, equities and real estate. Asset class performance is measured by quarterly series of total returns (see *Table A. 1* in *Appendix 1*).

B. Business and financial cycle

Table 1 provides an overview of five concepts to capture macro-financial cycles.

Two commonly used[31] signaling indicators characterize the business cycle:

- A univariate business index (***"GDP Index"***) based on real GDP growth[32] and
- A forward-looking multivariate[33] economic climate index (***"Economic Climate Index"***).

Trends in financial activity is investigated based on two continuous indicators, benefitting from recent work on financial cycles in general and relevant early warning properties to identify turning points more specifically (e.g. Borio (2012); Claessens et al. (2012); Drehmann et al. (2012); Aikman and other (2014); Alessi et al. (2014); ECB (2014); Stremmel (2015); Turner (2015); Claessens and Kose (2017b) and Filardo et al. (2018)):[34]

- A univariate financial cycle index based on credit growth[35] in the private non-financial sector and its level (***"Credit Index"***) and
- A multivariate financial cycle index that captures trends in credit to the private non-financial sector, asset prices[36] (equities, housing prices) as well as the level of credit-to-GDP[37] (see *Appendix 1*) (***"Financial Stability Index"***).

We also tested the performance of two purely market-based signaling index: a *risk parity index*, which targets a constant volatility level of 10% across four asset classes (equity, interest rates, commodities and credit) and a *valuation-based signaling indicator* depicting price-to-earnings ratios adjusted for cyclical developments. Both indicators, which were

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31 See OECD (2012) and the OECD website, for example.

32 The authors also tested equivalent indices based on nominal GDP and forward-looking industrial production growth, but those turned out to be inferior.

33 Economic climate indicators are by definition multivariate, given that the universe of relevant information can be factored in.

34 We also looked at the VIX as a candidate for a purely market-based financial cycle indicator and as an additional metric included in the multivariate model, but its univariate performance was poor (given a fairly low correlation with the asset price cycle), while its marginal contribution in the multivariate model was also largely absent. Further, we tested the usefulness of international capital flows (such as foreign credit) for the multivariate specification, but did not find evidence for the four economies that would warrant their inclusion.

35 The usefulness of (excessive) credit growth as a predictor of crisis has been documented in many studies, e.g. Gourinchas and Obstfeld (2012), Schularick and Taylor (2012).

36 The fact that the multivariate financial stability index includes the trend in asset prices is, statistically speaking, subject to collinearity (even when using lagged series); yet, this is not an issue as such for operational purposes (if rallying or dropping asset prices give a signal to re-allocation).

37 We have also looked at other indices, e.g. the financial cycle index used by the Drehmann et al., (2012), which turned out to be less useful for our purposes, given that the indicator does not include equity price trends.

only available for the US, yielded subordinate performance and are thus not considered further.

Table 1. Overview of signaling indicators and related concepts considered in this study

Indicator	**Description**
Business cycle indices (continuous)	
Univariate Business Index („GDP Index", GDPI)	• Raw series: quarterly y-o-y real GDP growth rates • Transformed series: multi-year cumulative growth rates (see *Table A. 3*) • Source: OECD
Multivariate Economic Index („Economic Climate Index", ECI)	• Raw series: Quarterly series of composite leading indicators • Transformed series: multi-year average (see *Table A. 3*) • Source: OECD
Business cycle indices ("quadrants")	
Growth/Inflation (G/I)	• Raw series: quarterly y-o-y real GDP growth rates and y-o-y inflation rates • Transformed series: trends in real GDP growth and inflation are compared to average levels observed during previous years (see *Table A. 3*) • Source: OECD data on GDP and inflation
Financial cycle indices (continuous)	
Univariate Financial Cycle Index („Credit Index", CI)	• Raw series: Credit growth to the private nonfinancial sector-to-GDP[38] and its level, based on a univariate binary logistic regression model • Transformed series: Change in raw series during multi-year horizon (see *Table A. 3*) • Source of data: BIS long-term series on credit to the private non-financial sector
Multivariate Financial Cycle Index („Financial Stability index", FSI)	• Raw series: Index established based on binary logistic regression analysis, using credit-to-GDP growth (at the 5-year horizon) and level of credit-to-GDP, equity index growth (at the 2-year horizon) and residential property price changes (at the 5-year horizon) as inputs; the output of the model (authors' computations, building upon IMF (2011b) is the likelihood for the occurrence of a financial crisis (banking crisis or severe drop in asset prices) within the next one to three year time horizon (for illustration see Appendix 1). • Transformed series: Change in raw series during multi-year time horizon (see *Table A. 3*) • Source of data: BIS long-term series on credit to the private non-financial sector, and house prices; equity data from the OECD.

Source: Authors

In addition to the growth-inflation regime, we benchmark the four continuous macro-financial cycles framework against asset allocation strategies used by institutional investors. For illustration, we refer to the "60/40" portfolio (60% equity, 40% sovereign

[38] Example: If credit-to-GDP grew from 100 to 150%, then we would use 50%.

bonds) and an "equity only" portfolio, which is used a benchmark for longer horizons.[39] We recognize that institutional investors use more dynamic and diversified asset allocation strategies, while noting that the average portfolio allocation of investment and pensions has been fluctuating around the 60/40 portfolio over time[40] (*Figure A. 8*, based on the OECD Institutional Investor Statistics[41]).

Figure 2 shows the four continuous signaling indicators (based on *Table 1*) along with the growth/inflation series. The panels display the raw (blue) and the transformed series of the signaling indicators both in- and out-of-sample (green/orange), along with the equity index (red) as a benchmark for the asset price cycles. The transformed series were constructed to maximize the out-of-sample performance, by choosing a favorable trade-off between trending and smoothing the signaling indicators on the one hand (making them more monotonic associated with less frequent asset re-balancing, and aligning their trend more closely to the equity price cycles) and retaining relevant patterns in the raw data on the other (i.e. avoiding time shifts and the removal of less defined stages altogether). Further information on the specification is given in *Appendix 1* and *Table A. 3*.

The graphs reveal that the turning points of all transformed series (green) broadly coincide with the downturns of the equity price cycles around 2000 and in 2007/8. At the same time, the series differ in terms of the broader patterns, and vis-à-vis equity price cycles. Since 2010, for example, equities have been constantly rallying, spurred by expansive monetary policies, which is not congruently picked by most macro-financial indicators.

Business cycles are found to be shorter than financial cycles and exhibit a lower amplitude. Between 1980 to 2018, both business cycle indicators (the in-sample series shown in green in the first row) go through five full cycles, compared to two/three (credit index) and four (Financial Stability Index) for the financial cycles (displayed in green in the middle row). This is akin to a cycle length of seven years (business cycle) and 9-14 years (financial cycles), which is in line with the findings of other studies (e.g., Claessens et al, 2012; ECB, 2014; IMF, 2017).

Yet, both types of cycles are clearly correlated, in the tradition of Minsky (1982) and Kindleberger (2000). In fact, several studies (Borio (2012); Claessens et al. (2012); IMF (2017); Claessens and Kose (2017b)) document that financial cycles are found to play an important role for business cycle recessions and vice versa (i.e., credit booms/credit contractions are reinforcing economic expansion/recessions), and that the relationship is stronger for advanced economies than for emerging market economies (Claessens and Kose, 2017b). The latter is likely the case due to fluctuations in the more developed financial markets being more relevant to the real economy, but probably also given that

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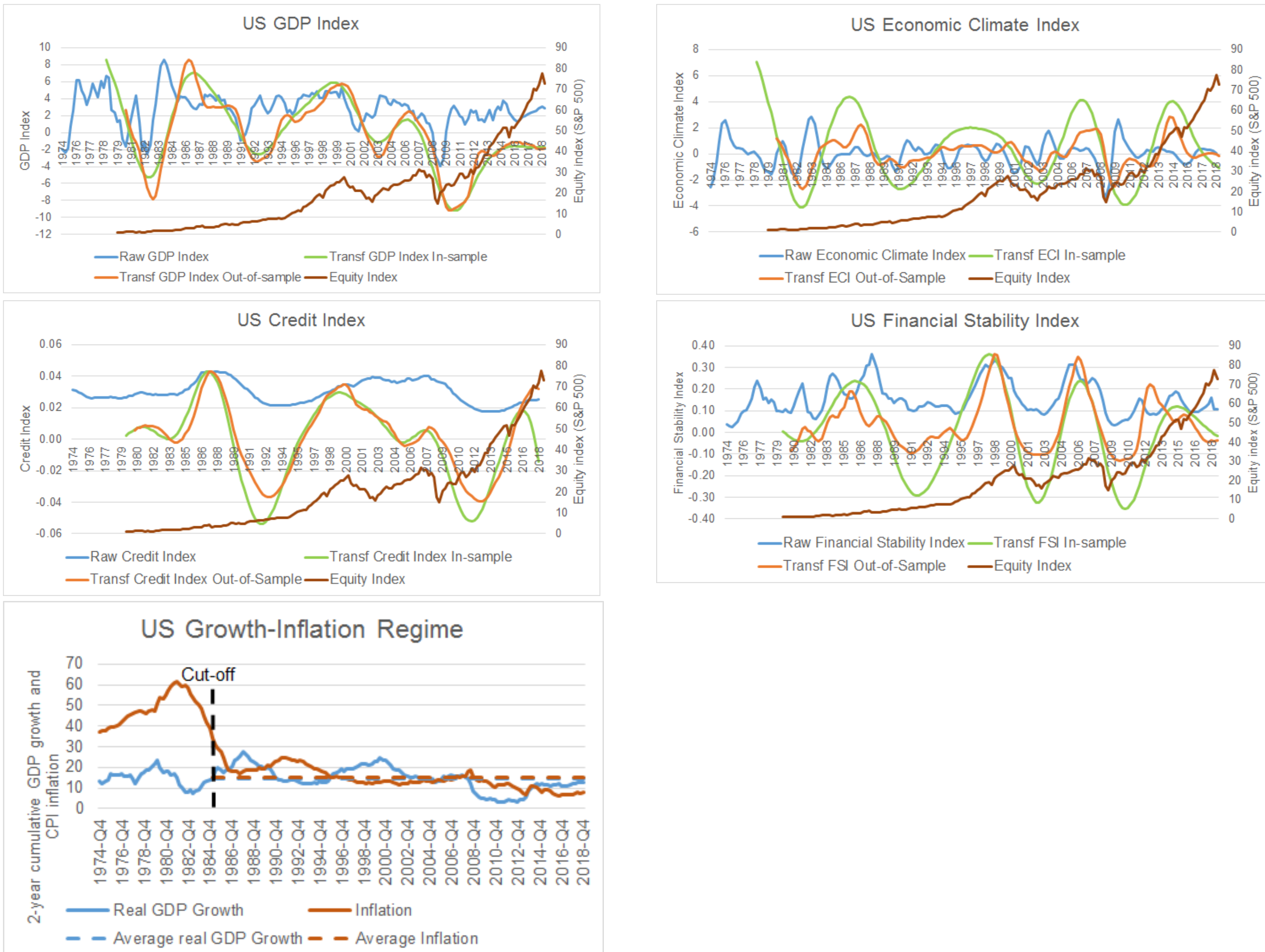
[39] Variations of this approach take into account economic growth, liquidity (money supply) and credit creation stance, risk appetite (captured by volatility and financial conditions), momentum and earnings (i.e. valuations such as price-to-earnings ratios) to deviate from the 60/40 percent mix.

[40] As shown in the Appendix, 60/40 constitutes a rather risky level for the strategic asset allocation followed by institutional investors in the four considered countries.

[41] See https://stats.oecd.org/BrandedView.aspx?oecd_bv_id=instinv-data-en&doi=c4292928-en#.

emerging market economies are more frequently affected by global shocks through international capital flows.

Figure 2. Time series of signaling indicators for the United States



Source: Authors

Note: The panels in the first two rows show the raw series (blue) along with the transformed series in- and out-of-sample (in-sample: green; out-of-sample: orange) and the equity index is displayed in red for reference; see Table 1 and Appendix 1 for further information on the construction of the series. The bottom left chart displays the series for the growth-inflation regime (note that the cut-off point marks a structural break in the raw series, and that we only use data post 1985 for calibration).

The series for the growth-inflation regime is displayed in the bottom row to the left, indicating that there is a structural break in 1985 for inflation, which is why we exclude earlier data from the analysis.[42]

In the final step, we map the transformed signaling indicators into stages of the cycle, as outlined in *Appendix 1*, using a classical definition of stages: we look at marginal changes in levels of economic and financial activity (as reflected in the signaling indicators) rather than at cycles based on the deviation of activity from trend, which makes the framework simpler, while it has been found to be effective to identify turning points (e.g. Claessens et al., 2011). Using changes in economic activity levels will also facilitate the robustness of the approach for the future given that trends. We only rely on observable macro-financial trends, recognizing the subordinate track record of macroeconomic forecasting.[43] For the growth-inflation regime, the stages reflect whether growth and inflation are above or below the long-term average for 1985-2018.

V. Macro-based approach to asset allocation: Applied example

A. Specification of in- and out-of-sample analysis

Table 2 compares the core building blocks of the framework in- and out-of-sample, suggesting two main differences (highlighted in dark grey): (i) one is the technique to extract trends for the signaling indicators, which is straightforward for in-sample analyses while it poses a major challenge in real time out-of-sample conditions; and (ii) the other one is the calibration of portfolio weights, which is based on perfect ex post knowledge in-sample, while it only captures information up to the respective point in time in real time.

Table 2. Specification of core elements for the in-sample and out-of-sample analysis

Element		In-sample analysis	Real time / out-of-sample analysis
Signaling indicators	Calibration	FSI and CI calibrated based on full series (1980-2015)	FSI and CI calibrated based on full series (as models based on 1980-2000 data exhibits very similar coefficients)
	Extraction of trend (transformation)	Trend extraction from raw series to maximize in-sample performance using two-sided HP-filter	Trend extraction from raw series to maximize out-of-sample performance using exponentially weighted average

[42] The observation that absolute levels of various parameters can change (i.e. that they may not be stationary) is the reason why we look at changes in signaling indicators rather than levels, and will likely yield more robust results in the future (in case of structural changes).

[43] See, e.g., An et al. (2018) and FT ("IMF shows poor track record at forecasting recessions", as of April 9, 2018).

	Stages	Use of rule of thumb to smooth the sequence of stages (see *Appendix 1*)	Use of rule of thumb to smooth the sequence of stages (see *Appendix 1*)
Growth/Inflation	Stages	Threshold for growth / inflation stages determined ex post, rule of thumb to smooth the sequence of stages	Threshold for growth / inflation stages determined in real time, using the last 10 years of observations, rule of thumb to smooth the sequence of stages
Asset allocation rule	Specification and calibration	Balanced and concentrated portfolio established based on ex-post information on average returns for each asset and stage (benchmark: mean-variance optimized portfolio)	Balanced and concentrated portfolio established based on average returns for each asset and stage computed based on information available at specific point in time (benchmark: mean-variance optimized portfolio)
Data	Ex post revisions	Not applicable	Not considered given the lack of such data, but assumed to be of subordinate importance

Source: Authors

B. Asset returns conditional on the stages of the cycle

A natural objective of any investor engaged in macro-based asset allocation would be to invest in the asset classes with the highest expected returns during the respective stages of the cycle and to re-balance the portfolio in favor of other asset classes that outperform during other times. Anticipating turning points to re-balance assets is particularly relevant ahead of sharp market drops (albeit not "too early") – to avoid losses – as well as around the time when recovery begins – to avoid opportunity costs by missing out on in recovery phases. The central question addressed in this paper is to analyze whether there is a meaningful (i.e. recurring) asset class performance during different cycle stages which investors can build upon.

It turned out that a few assets clearly outperform other assets during the different stages of the cycle (*Table 3* - *Table 6* and *Appendix 2*). In fact, one of the defining features of macro-based asset allocation is to be able to put many (though not all—given that it is impossible to precisely anticipate turning points) eggs into the same basket in good times, and to re-allocate most assets before the asset price cycle turns. For illustration, we use a pragmatic asset allocation rule as outlined in *Appendix 1*, and refer to a *balanced portfolio,* a *moderately concentrated* and a *concentrated portfolio*.

Table 3 shows the asset allocation for the ECI. In-sample, asset allocation is as expected, reflected in high performance (*Figure 3*, upper panel):

- During contraction periods, the framework foresees substantial investment in sovereign bonds, supplemented by investment grade (IG) corporates and cash.
- In recovery and expansion phases, one would invest most funds into real estate, supplemented by equity and high yield (HY) corporate bonds.
- During slowdowns, most of the investment goes into equity, supplemented by real estate and HY corporate bonds.

Out-of-sample, the asset allocation is stage-shifted and commodities take a prominent share. Specifically, the "contraction" phase corresponds to the recovery phase in the in-sample specification, led by real estate investment, while the slowdown phase includes a high portion of equity as a late cycle element both in- and out-of-sample, but also sovereign bonds as an element of contraction phases out-of-sample. During the recovery and expansion phase, commodities are the dominant asset class together with equities and real estate. Hence, as also illustratively shown in *Figure 2*, the extraction of the long-term trend based on this indicator was apparently not smooth enough to apply our framework in real time, given the volatility of the raw index, despite the use of long-term trends.

Table 3. Asset allocation for the Economic Climate Index for the United States

In-sample asset allocation (by 2018) (balanced portfolio)								
Stage	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	2%	0%	12%	0%	7%	60%	20%	0%
Recovery	0%	66%	0%	3%	19%	0%	5%	7%
Expansion	0%	52%	0%	0%	21%	1%	2%	24%
Slowdown	0%	31%	0%	0%	52%	3%	2%	12%
Real-time out-of-sample asset allocation (by 2018) (balanced portfolio)								
Stage	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%	54%	0%	0%	11%	9%	7%	19%
Recovery	1%	22%	0%	44%	31%	0%	0%	1%
Expansion	0%	23%	0%	41%	27%	0%	1%	9%
Slowdown	0%	4%	0%	0%	40%	24%	13%	20%

Source: Authors

Note: For a definition of stages see section IV.B. Further information is provided in the appendices. The table shows the calibrated asset allocation by end 2018.

For the FSI, asset allocation is fairly similar in- and out-of sample, and is reflected in the highest out-of-sample performance among all indicators since 1995 and 2000 (*Figure 3*), respectively. As shown in *Table 4* for the balanced portfolio, real estate is the dominant asset class during recovery, along with HY corporates. During expansion, investment is dominated by real estate and equities. The slowdown phase is clearly dominated by equities. During contraction, commodities are the leading asset class for the FSI. Bonds also contribute 5-50% of the share across all stages. The concentrated portfolio boosts annual total returns out-of-sample to 13.8% since 1995, up from 11.7% for the balanced portfolio.

Table 4. Asset allocation for the Financial Stability Index: in-sample vs real time out-of-sample for the United States

In-sample asset allocation (by 2018) (balanced portfolio)								
Stage	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%	0%	3%	81%	0%	11%	5%	0%
Recovery	0%	41%	0%	0%	0%	12%	19%	28%
Expansion	0%	46%	0%	3%	35%	0%	0%	16%
Slowdown	0%	12%	0%	0%	72%	7%	3%	7%
Real-time out-of-sample asset allocation (by 2018) (balanced portfolio)								
Stage	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	3%	0%	0%	76%	18%	0%	0%	3%
Recovery	0%	49%	0%	0%	4%	9%	12%	25%
Expansion	0%	25%	0%	0%	44%	13%	6%	11%
Slowdown	0%	12%	0%	5%	78%	1%	0%	4%

In-sample asset allocation (by 2018) (concentrated portfolio)								
Stage	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%	0%	0%	97%	0%	3%	0%	0%
Recovery	0%	81%	0%	0%	0%	0%	0%	19%
Expansion	0%	71%	0%	0%	29%	0%	0%	0%
Slowdown	0%	3%	0%	0%	97%	0%	0%	0%
Real-time out-of-sample asset allocation (by 2018) (concentrated portfolio)								
Stage	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%	0%	0%	91%	9%	0%	0%	0%
Recovery	0%	86%	0%	0%	0%	0%	0%	14%
Expansion	0%	17%	0%	0%	83%	0%	0%	0%
Slowdown	0%	4%	0%	0%	96%	0%	0%	0%

Source: Authors

Note: For a definition of stages see section IV.B. Further information is provided in the appendices. The table shows the calibrated asset allocation by end 2018.

For the FSI, not only is the real-time out-of-sample asset allocation pattern similar to the in-sample specification but also over time, as documented in *Table 5* for the first, second and third asset price cycle (as per the turning points of the US equity index, see *Figure A. 1*). The differences in asset allocation compared to *Table 4* stem from the fact that the previous table shows the asset allocation an investor would use at end-2018, suggesting that gold, commodities and bonds lost some ground compared to earlier periods, while real estate and equities climbed up, mirroring their strong performance in recent years.

Table 5. Asset allocation for the Financial Stability Index out-of-sample for different asset price cycles for the United States (balanced portfolio)

Asset allocation for real-time out-of-sample analysis during Q1/1995-Q3/2000 (1st asset price cycle)								
Stage	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%	0%	2%	60%	27%	0%	4%	7%
Recovery	0%	34%	0%	0%	9%	3%	6%	49%
Expansion	0%	2%	0%	0%	33%	31%	21%	12%
Slowdown	7%	21%	0%	15%	51%	6%	0%	0%
Asset allocation for real-time out-of-sample analysis during Q4/2000-Q2/2007 (2nd asset price cycle)								
Stage	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%	0%	1%	76%	19%	0%	1%	2%
Recovery	0%	38%	0%	0%	4%	10%	14%	34%
Expansion	0%	7%	0%	0%	50%	22%	13%	9%
Slowdown	10%	4%	0%	27%	54%	6%	0%	0%
Asset allocation for real-time out-of-sample analysis during Q3/2007-Q4/2018 (3rd asset price cycle)								

Stage	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	1%	0%	1%	82%	13%	0%	1%	1%
Recovery	0%	44%	0%	0%	2%	12%	14%	29%
Expansion	0%	18%	0%	0%	47%	19%	8%	7%
Slowdown	6%	16%	0%	7%	68%	2%	0%	0%

Source: Authors

Note: For a definition of stages see section IV.B. Further information is provided in the appendices. The table shows the calibrated asset allocation at the end of the respective period.

The portfolio composition for the growth/inflation regime is displayed in *Table 6*. For some stages, the portfolios differ quite substantially between the in-sample and out-of-sample, reflecting changes in the cut-off points for growth and inflation over time for the real-time analysis. In-sample, equities are the dominant asset class during periods of high growth and inflation along with commodities, for example, while real estate and equities dominate out-of-sample. Using a binary threshold to divide the cycle into stages is a straightforward concept, but will unlikely anticipate structural breaks which constitutes a caveat for the application of the growth/inflation regime.

Table 6: Asset allocation for the Growth/Inflation regime for the United States

In-sample asset allocation (by 2018) (balanced portfolio)								
Stage	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
ng_ni	0%	43%	0%	0%	36%	0%	3%	17%
ng_i	0%	43%	0%	0%	3%	13%	11%	30%
g_ni	0%	20%	0%	78%	1%	0%	1%	0%
g_i	0%	1%	0%	25%	66%	6%	3%	0%
Real-time out-of-sample asset allocation (by 2018) (balanced portfolio)								
Stage	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
ng_ni	0%	61%	0%	6%	7%	0%	0%	25%
ng_i	0%	21%	0%	0%	1%	27%	22%	29%
g_ni	0%	10%	0%	0%	71%	8%	7%	4%
g_i	19%	43%	0%	1%	36%	0%	0%	2%

Source: Authors

Note: "g_n" is when the trends for both growth and inflation are above the long-term average for 1985-2018 (in-sample); 1985-point in time (out-of-sample); "g_ni": growth is above average but inflation below; "ng_i" is low growth paired with high inflation and "ng_ni" is low growth paired with low inflation.

The asset allocation for the balanced portfolios for the universe of specifications considered in this study for all four countries is documented in *Appendix 2*, along with the asset returns and their standard deviation. For the FSIs, which yield the strongest performance in all four jurisdictions (*Figure 3*), asset allocation is generally in line with expectations, i.e. we find that (i) the high yielding asset classes (equities and real estate, and, to a lesser degree, HY corporates) should be strongly overweighed during upswings of the financial cycle (i.e., expansion and slowdown, but also recovery), while (ii) safe assets (sovereign bonds, cash, investment grade corporates) and countercyclical asset classes (commodities, gold) dominate during periods of contraction. For some of the most promising specifications, the portfolio composition is fairly similar across upturn stages (recovery, expansion, slowdown), which could motivate the use of a 2-stage concept in addition to four stages (lowering transaction costs). It is also clearly documented that inferior performance is often associated with non-intuitive asset allocation patterns, given the lack of a robust relationship between macro-financial cycles and asset price cycles.

C. Performance

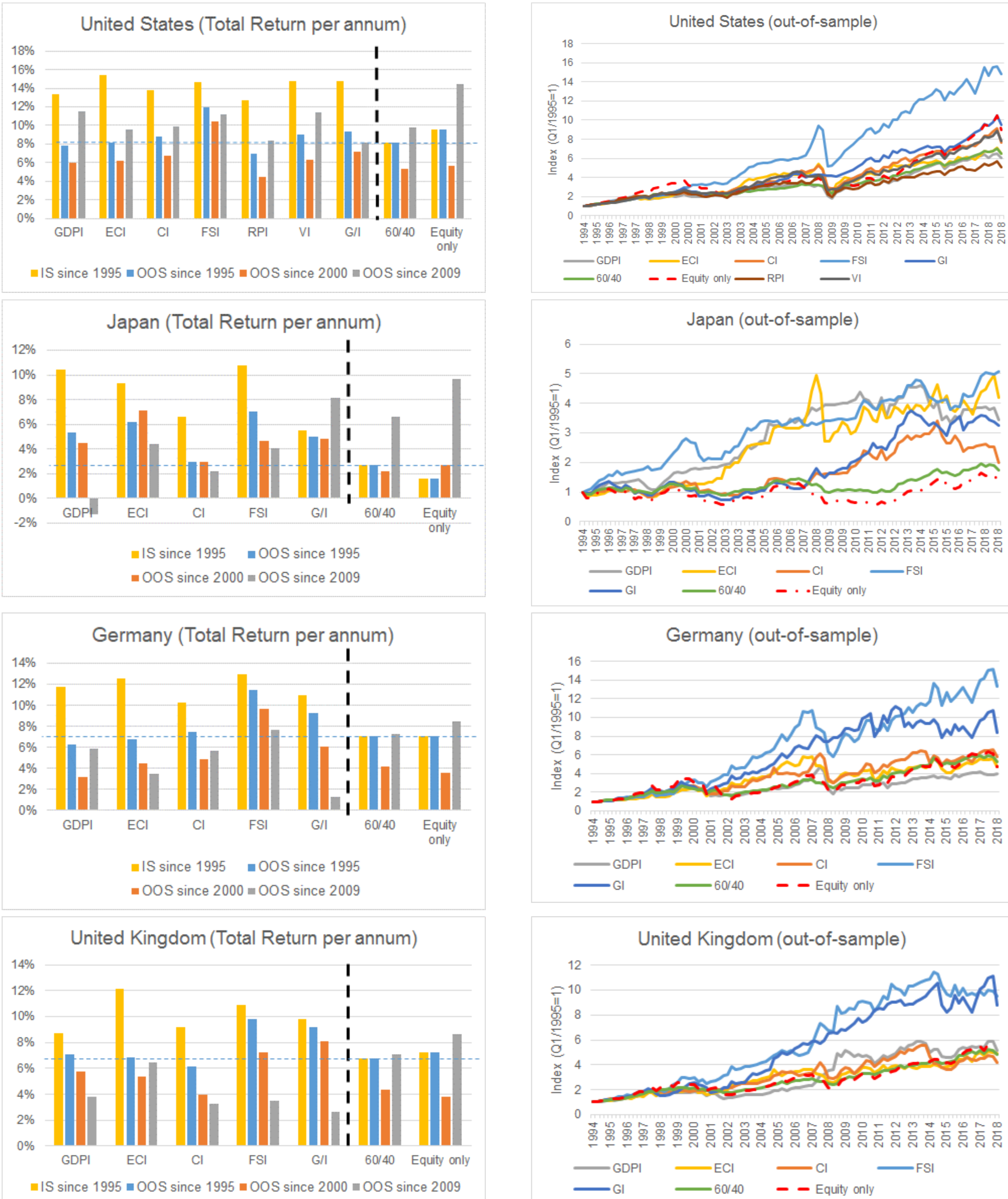
The eight panels in *Figure 3* display the final outcome of our real time out-of-sample analysis based on moderately concentrated portfolios for three periods: 1995-2018 (dark blue bars in left panels and right hand graphs); 2000-2018 (orange bars); and 2009-2018 (grey bars). For the longest period (i.e. 1995-2018), we add the in-sample performance (in light blue), indicating the potential performance of the indices under "ideal" conditions. The left hand graphs display the total return per annum (ATR), while the right hand charts are index based.

Figure 3 provides answers to central questions addressed in this study:

- The macro-based strategies investigated in this study tend to be superior to commonly applied strategies by institutional investors (which foresee fairly fixed asset allocation strategies), especially for longer time periods. A key strength of macro-based asset allocation is that elevated returns come along with contained volatility.
- The signaling indices differ in terms of their performance, suggesting that multivariate indices trump univariate ones (i.e., FSI vs CI; ECI vs GDPI).
- The outcome is fairly consistent across the four countries: the FSI yields the strongest performance among all indices, followed by the growth/inflation regime.
- Real time out-of-sample performance is substantially lower than potential (i.e. in-sample) performance, and the gap is smaller for slow moving indices.

Performance varies over time, depending on whether and how the indices capture the distinct turning points. During recent years (i.e. since 2009), equities have been rallying constantly (thanks to accommodative monetary policies and generally favorable macro-financial conditions and), while most indicators continued to signal varying macro-financial conditions and asset allocations, respectively (*Figure 2*). Hence, equity-only strategies would have been most successful during that period in all four countries, while the performance of the signaling indices has been roughly at par with the 60/40 strategy.

Figure 3. Portfolio performance under real time out-of-sample conditions (1995-2018)



Source: Authors

Legend: "GDPI": GDP Index; "ECI": Economic Climate Index; "CI": Credit Index; "FSI": Financial Stability Index; "G/I": Growth/Inflation; "IS": in-sample; "OOS": out-of-sample;

Note: The left hand charts display the annual total return (ATR, in percent). To the right, portfolio performance for each period is indexed at the beginning of the time horizon covered by the simulation (i.e. for 1995-2018 at 1 by 12/1994), using a moderately concentrated asset allocation and a transaction fee of 0.5% to adjust the asset allocation. Further information is provided in the appendices.

Using the most concentrated portfolio allocation studied herein (not shown), the FSI would be roughly at par with the equity-only strategy since 2009 (ATR: 13.7% vs 14.4% for equity only), while the performance of the GDPI (13.7%) would also improve quite substantially, while the performance for the G/I regime (8.4%) would drop sharply compared to the moderate portfolio concentration.

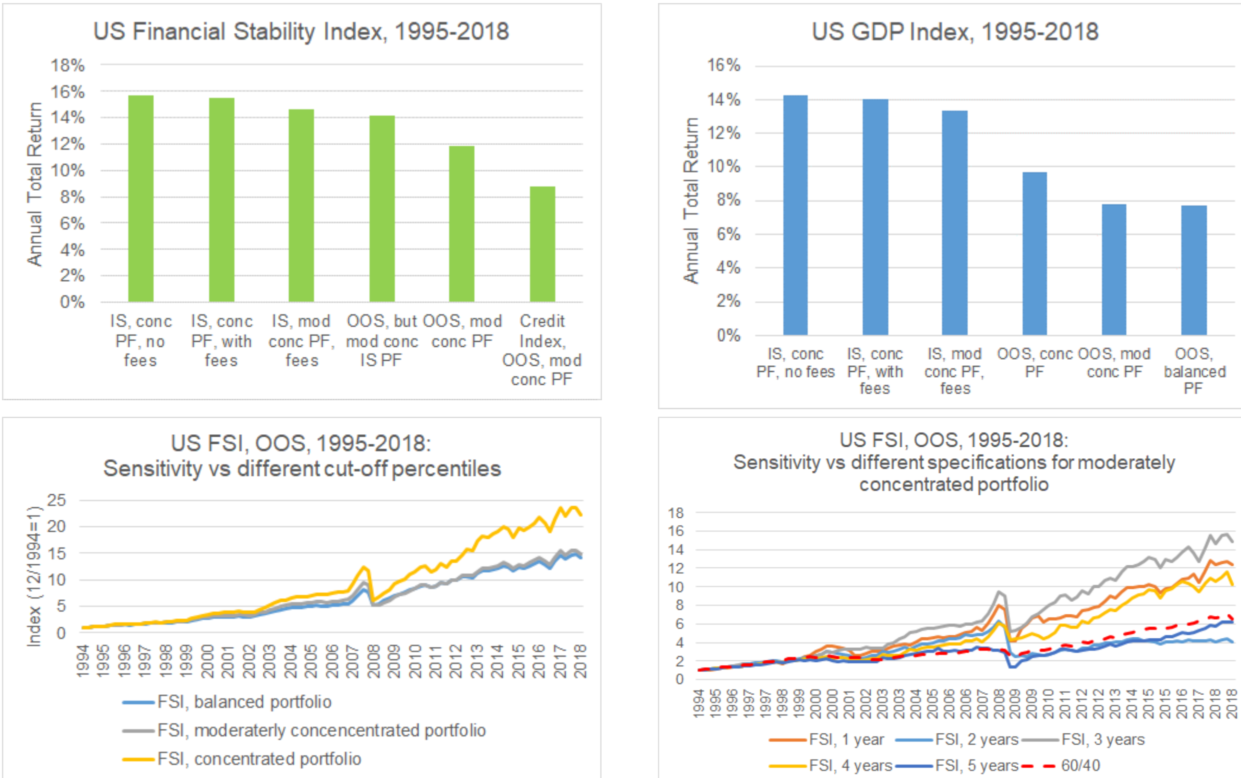
The portfolio allocations and key performance metrics (ATR, standard deviation, Sharpe ratio) are displayed in *Appendix 2*. Performance tends to increase for more concentrated asset allocation strategies (including putting all eggs into the supposedly most successful asset class), suggesting that the signaling indicators are fairly well calibrated, although there are substantial variations across the specifications. A key strength of macro-based asset allocation is that elevated returns come along with contained volatility, as reflected in the Sharpe ratios. While still superior compared to other concepts, we find that the framework is least successful for Japan.

D. Determinants of performance and robustness

Figure 4 provides a selection of illustrative examples to document the relative importance of different factors on performance, but also to indicate the robustness of the findings at the example of the FSI (left panel) and the GDPI (right panel) for the US during 1995-2018. For the FSI, in the "ideal" case, i.e. in-sample, without fees and based on concentrated asset allocation the ATR is at 15.7% (left green bar in left panel). The introduction of transaction fees for portfolio re-allocation reduces performance to 15.5% and less concentrated asset allocation to 14.7%. In the out-of-sample case, ex post knowledge on the asset performance would yield a return of 14.2%, which drops to 13.8% for real time asset allocation and further to 11.9% for moderate portfolio concentration and to 11.7% for the balanced portfolio. At the same time, the performance of the multivariate FSI yields twice the performance of the univariate credit index (CI), which is at 8.8% (the green bar to the right of the left chart).

For the GDPI, the relative impact of fees and less concentrated asset allocation is fairly similar as for the FSI (ideal case: 14.3%), but out-of-sample performance drops to 9.7% for the concentrated portfolio and to 7.8% (moderately concentrated portfolio) and 7.7%, respectively, for more balanced portfolios.

Figure 4. Illustrative examples on the relative importance of different determinants



Source: Authors

Note: "IS": in-sample; "OOS": out-of-sample; "FSI": Financial Stability Index; "FSI (LV only)", "FSI (LV & EP)": FSI index with dependent variable banking crisis or banking crises and severe equity price drops (see Appendix 1).

Table 7 summarizes our findings on the relevance of different determinants, based on the universe of descriptive evidence across the various specifications.[44] These findings suggest that the two defining determinants of performance are (i) the economic (early warning) properties of the signaling indicators as well as (ii) the robustness of the specifications to link trends in the signaling indicator to asset return cycles. Across the various specifications, the scope of information captured by the signaling indicator is found to be advantageous (multivariate vs. univariate, i.e. their economic properties). Moreover, for at least some of the specifications, the impact of using a two stage[45] framework rather than four stages yields comparably limited losses in performance and could be considered as an element to keep things simple, including when the calibration period is short. Operational elements of the indicators (i.e., the timely availability of data for real time analysis, transaction costs and the choice of asset allocation rules) are found to be less impactful.[46]

[44] We did not attempt to test econometrically the economic and statistical significance of the different determinants.

[45] i.e. contraction and upturn (recovery or expansion or slowdown).

[46] We did not consider data robustness (e.g. likelihood of revisions later on) (see OECD, 2012).

Table 7. Determinants of performance

Driver	Determinant	Impact
Signaling indicators	General economic properties	+++ • Multivariate indicators trump univariate indicators with respect to their signaling properties, i.e. breadth of information captured by indices facilitates performance and will likely improve robustness
	Robustness of specification	+++ • Extracting trends is more straightforward for less volatile indicators, also given that asset price cycles follow a fairly steady cycle • Number of stages: using four stages tends to be superior in general and for longer time horizons (to calibrate the portfolios), but in some cases the gap is limited (e.g. for the FSI in the specification shown in *Figure 4*)
	Operational properties	+ • The timeliness of the availability of the indicators and their frequency do not seem to have a strong impact on performance, given that the extraction of trends for the signaling indicators accounts for those factors
Asset returns	Transaction costs	+ • Transaction costs to re-allocate funds have a limited impact (of about 2% on annual total returns in the illustrative example above)
Asset allocation	Rules	+ • Asset allocation tends be concentrated by definition, hence there is a limited impact of using different asset allocation rules; to avoid losses, it is more important to choose indicators with strong signaling properties than seeking diversification conditional on the stages • Longer calibration periods for the asset allocation for different stages are useful, but did not turn out to be a game-changer

Source: Authors

Note: "+++": high impact; "++": medium impact; "+": low impact; 0: no impact

What will happen in the worst case?

It is challenging to predict in advance what would happen if the relationship between signaling indicators and asset price cycles were to change or if asset returns were subject to a structural change, whereby the concept presented in this study could be compromised. As a means of illustration, the bottom right panel in *Figure 4* documents the sizeable impact of the specification for the FSI: The out-of-sample FSI specification yielded an annual total return of 11.9%, compared to 8.1% for the 60/40% portfolio, while the specifications for the other signaling variables displayed in the graph yield between 7% and 10%.[47] Looking across the whole range of potential specifications (e.g. using "wrong" trends which do not properly capture turning points) the performance for the FSI drops to the level of the 60/40 portfolio or slightly below, which might give an indication of performance subject to unfavorable calibration.

Elements to hedge performance include (i) the use of indicators calibrated to reflect shorter time trends to identify turning points; (ii) application of indicators with forward-looking properties (such as the ECI and, to a lesser extent, the FSI); and (iii) risk-adjusted asset allocation rules.

VI. Conclusion

This study explored the usefulness of different continuous indicators characterizing business and financial cycles for (macro-based) asset allocation purposes, benefitting from recent advances in the early warning literature to detect financial stability risks. We find fairly robust links between asset price cycles and macro-financial cycles during the past three decades.

In the market environment since the mid-1990s, characterized by volatile conditions and increasing levels of financial integration, the pursuit of such a concept opens up opportunities. Yet, superior performance might suffer if the observed relationship between asset price cycles and business/financial cycles were to change. Unconventional monetary policy is one element that has had an important bearing on the asset performance in recent years, for example, along with other conjunctural factors such as risk aversion and search for yield. Other relevant drivers are changes in market structures, which can be conjunctural or structural (e.g. demographics leading to asset accumulation), along with regulatory changes adopted since the financial crisis.

Our analysis reveals that the concept presented herein appears to be useful if benchmarked against other common approaches used by institutional investors, both in terms of actual returns and portfolio volatility. The most important determinant for differences in performance are the economic properties of the cycle indicators, as expected. More sophisticated concepts to measure cycles (multivariate approaches vs univariate ones) are shown to be more valuable. Conceptual advancements to reduce the gap between the ex-post performance (i.e. investment based on perfect knowledge in hindsight) and real time performance would be beneficial, although pragmatic approaches as illustrated herein could serve as a starting point. The findings for Japan also documents that the concept can be useful in a macro-financial environment characterized by low yields for fixed income

[47] Growth-Inflation: 9.9%; VI: 9%; CI: 8.8%, ECI: 8.1%, GDPI: 7.8%, RPI: 7%.

securities and stagnating equity prices, although it turned out to be more challenging as for the other countries.

We note a few important points. First, we sought to present a concept based on an applied example rather than optimize actual specifications. Hence, the asset allocation provided herein is illustrative. Second, the key question for the usefulness of the concept is whether the relationships between business and financial cycles on the one hand and asset price cycles on the other will be similar as observed in the past. To this end, we have indicated specific elements that could contribute to hedging performance (in section V.D).

The implications of this work is two-fold: for medium- and long-term investors, macro-based asset allocation is a promising avenue to follow, but requires a robust framework to anticipate turning points (also given that asset allocation is concentrated by definition); and from a financial stability angle, it would be desirable to better understand the dynamic link between asset prices and cyclical conditions, as the former is an amplifying driver for macroeconomic and financial downturns and vice versa.

There are a number of challenges to be further elaborated: one is how to operationalize macro-based asset allocation, such as the availability of meaningful real time information. Other challenges include the role of liquidity, which has not been explored explicitly herein, and could prevent re-balancing of less liquid positions during periods of stress when cyclical indicators would suggest doing so, or at excessive costs.[48] Combining information from business cycle and financial cycle indicators could be very useful, and increase the robustness of macro-based asset allocation frameworks.[49]

[48] See the numerous discussions of market liquidity in recent years.

[49] We combined the two-stage inputs of both indicators (e.g., for a specific point in time, an upturn for the business cycle and a downturn for the financial cycle), and determined performance for four combined macro-financial stages. We also included business cycle information into the financial cycle models, but it turned out that the combined indices did not produce superior performance using fairly simple specifications. Yet, combined indices appear to be a promising element to study.

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Appendix 1. Technical appendix: Overview of framework used in this study

Step 1: Collection of asset returns

Asset class performance is measured by quarterly series of total returns[50], which are the same for commodities and gold.

Table A. 1 Asset class data: Description and Source

Asset Class	Germany	Japan	United Kingdom	United States
Commodities	S&P GSCI commodity index (S&P GSCI Commodity Total Return - RETURN IND. (OFCL), GSCITOT (TR))			
Gold	Gold price index (Gold Bullion LBM U$/Troy Ounce, S20665 (P))			
Cash	Long-term series on Short-term interest rates by OECD, complemented, where not available, by data from IMF IFS on Treasury Bills rates			BOFA US 3-month Treasury bill index (MLUS3MT (RI))
Corporate Bonds (IG)	Bloomberg Barclays Total Return Index for German Corporates (LHGCDE$(IN))	BofAML Total Return Index for Japanese Corporates (MLJPCPY (RI))	BofAML Total Return Index for BBB Sterling Corporate (ML£3BTL (RI))	BOFA Total Return Index for IG corporates (MLE$5I$ (RI))
Corporate Bonds (HY)	N/A	N/A	N/A	BOFA Total Return Index for HY corporates (MLH100$ (RI))
Equity	Dax 30 total returns (DAXINDX (RI))	Nikkei 250 Total Return Index (TOKYOSE (RI))	FTSE 100 Total Return Index (FTSE100 (RI))	S&P 500 total returns (S&PCOMP (RI))
Government Bonds	N/A[51]	Total Return Index for 10 year gov. bonds (BMJP10Y (RI))	Total Return Index for 10 year gov. bonds (BMUK10Y (RI))	BOFA Total Return Index for 7-10 yr Treasuries (GSCITOT (TR))
Real Estate	N/A	N/A	N/A	FTSE NAREIT composite index (NARALL$ (RI))

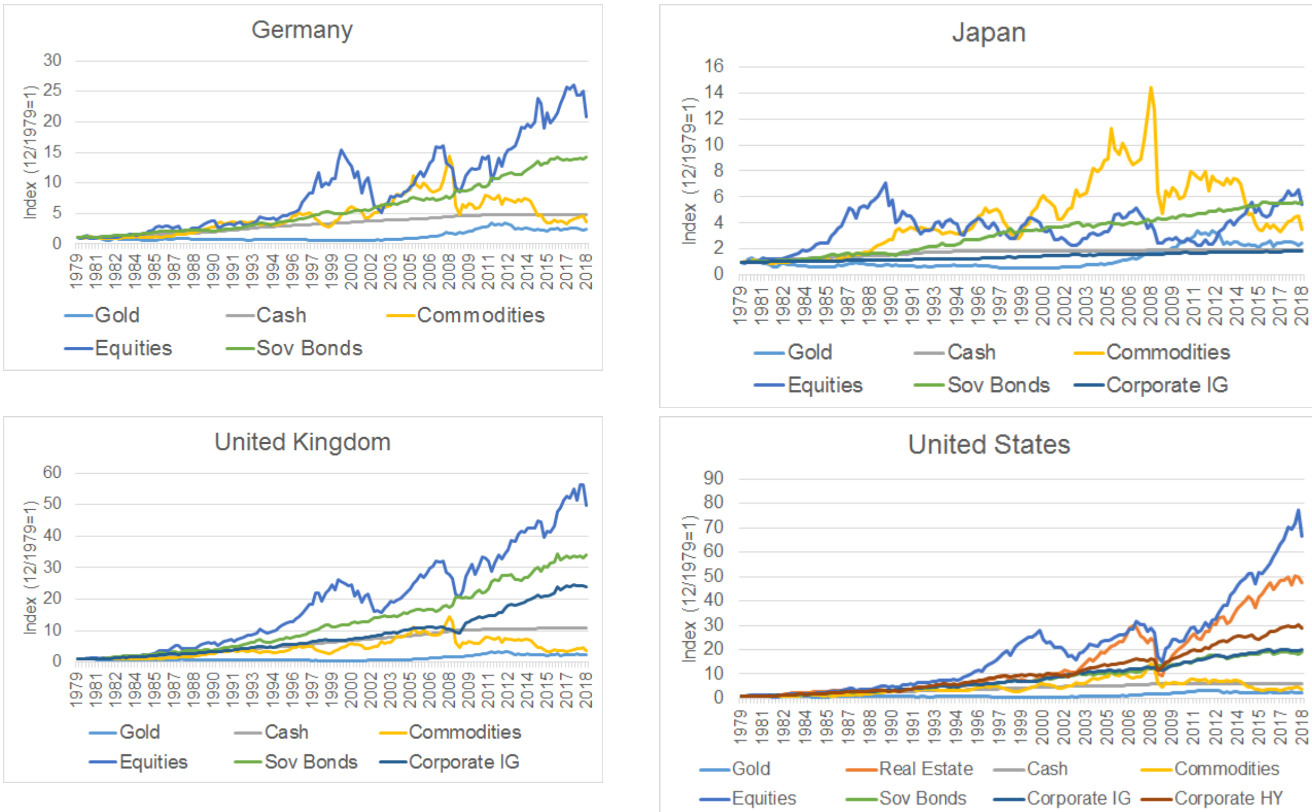
Note: Short data gaps were filled through comparison with meaningful benchmark series. Source: Thomson Reuters Datastream

[50] We use end-of-the period data to determine asset class performance, based on the stages of the cycle identified by the end of the previous quarter. For some of the signaling indicators (e.g., the Economic Climate Index), we could also use monthly asset return data, matching the frequency of the indicator.

[51] The available time series (Total Return Index for 10 year gov. bonds (BMBD10Y (RI))) are too short.

The total returns for all series are shown below.

Figure A. 1: Asset Class Total Returns (1980-2018) (Q4/1979=1)



Source: Authors, based on data from Thomson Reuters

Step 1: Establish signaling indicators

Table 1 provides an overview of the four signaling indicators used in this study, along with an outline of the growth/inflation regime. Below, we provide more information on the Financial Stability Index (FSI).

Financial stability index (FSI)

The multivariate FSI was established as follows: We use data by Laeven and Valencia (2012) to identify the beginning of systemic banking crisis ("LV"), while equity price shocks are characterized by drops of equity indices by more than 15% within one quarter.[52] Accordingly, we classify all observations one to three years prior to such events as crisis-related observations and all other observations as non-crisis observations, except for the observations at the time of the crisis and the subsequent two years, which are excluded from the analysis. We use one model with banking crises dummies as the dependent variable and another one with dummies signaling either banking crises or equity price shocks.

[52] We also used other thresholds for robustness purposes.

The model is built on data for 34 advanced economies, which experienced[27] systemic banking crises from 1970-2015 and 171 instances of severe drops of equity prices, based on a total of 1,564 observations of annual data. We tested a number of specifications, benchmarking our results with other studies (e.g. Alessi et al., 2014). Information on the statistical specification is tabulated below. Shorter models based on data from 1970-2000 yielded similar results in terms of the coefficients, R-squared and ROC characteristics, although with slightly lower significance levels for house price and equity price growth.

Logistic regression analysis based on annual data (1970-2018), from 34 advanced economies

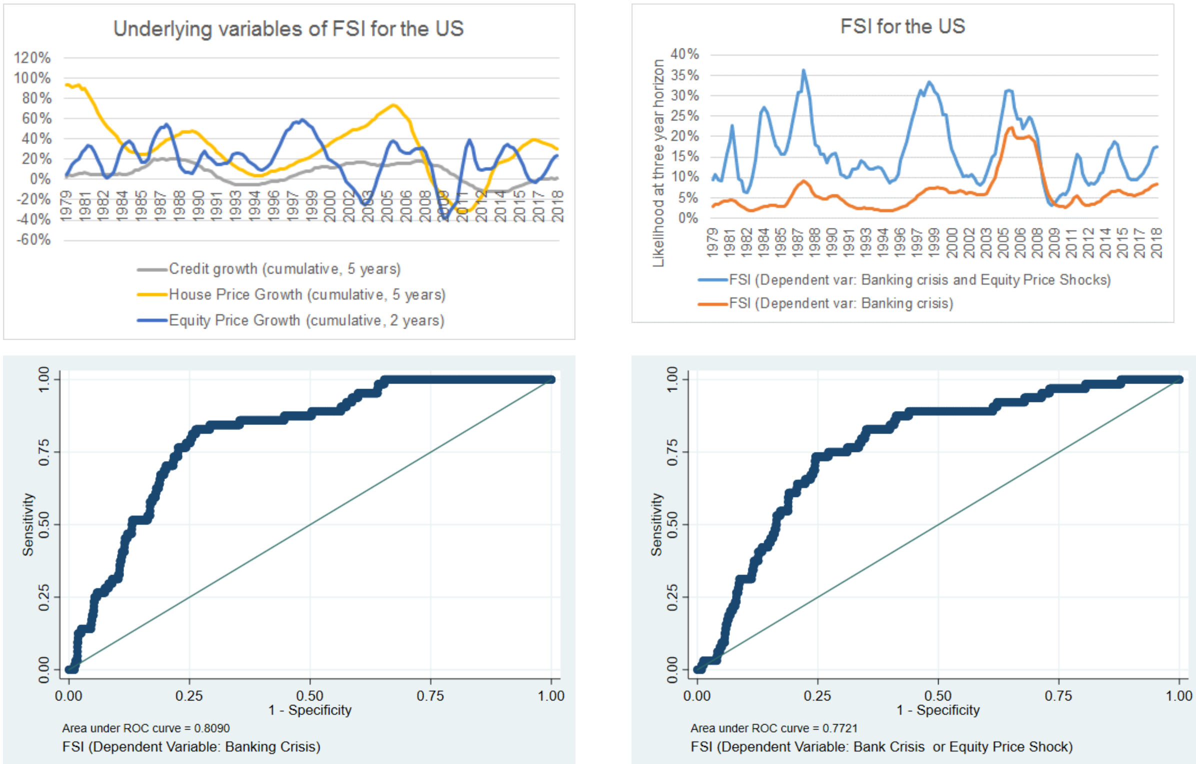
Dependent variable Variables	LV (Banking crises dummy) ("LV only")	LV (Banking crises dummy) or severe equity price shock ("LV and EP")
Credit-to-GDP growth[53] (t vs t-5)	+***	+***
Credit-to-GDP level	+***	+***
House Price growth (t vs t-5)	+**	+*
Equity Price growth (t vs t-2)	+***	+***
Constant	-***	-**
R-squared	0.16	0.14
Observations	708	548
T (Annual observations)	46	46

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

The panels below show the development of the underlying series for the United States – credit growth (based on credit-to-GDP for the private non-financial sector) as well as growth of house prices and equity prices, along with the two resulting multivariate indices and their goodness of fit properties – the area under the curve plots and metrics.

[53] We use data for credit to the private non-financial sector.

Figure A. 2: FSI: underlying series and goodness of fit statistics



Source: Authors.

Top left panel: Evolution of underlying explanatory variables (except for the credit-to-GDP level). Top right panel: FSIs for dependent variable reflecting banking crisis "only" as well as banking crisis or sharp equity price shock – the latter of which is also shown in Figure 2.

Panels in bottom row: Receiver operating characteristic (ROC) and area under the ROC curve statistic of 0.8 and higher indicate solid fit properties for the model. We also estimated models based on data from 1970-2000 with similar ROC properties.

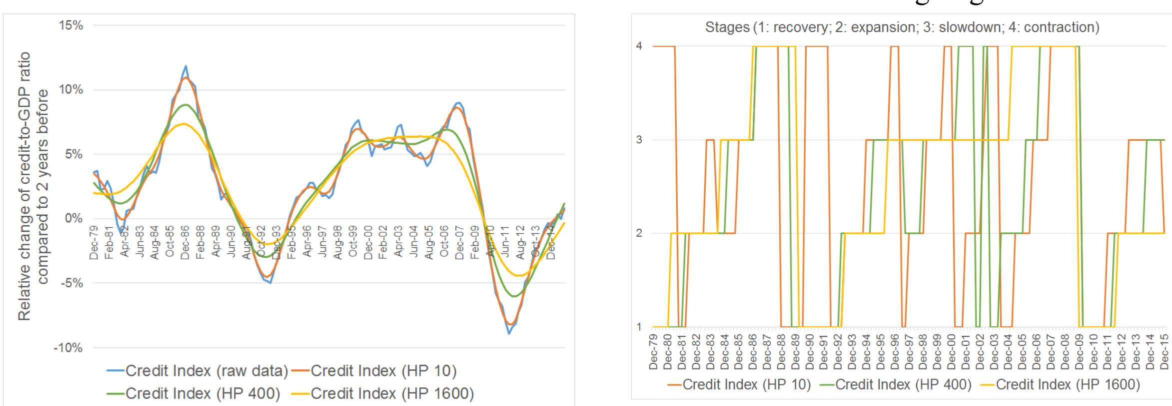
Step 2: Establishment of stages

We apply a classical definition of stages, i.e., look at changes in levels of economic and financial activity rather than at cycles based on the deviation of activity from trend (see Claessens et al (2011), for example. The stages are determined by computing the marginal change of the respective index, both in terms of the sign (increasing/decreasing) and slope (marginal increase positive or negative).

Figure A. 3 illustrates the concept. As shown in the left hand panel, smoothing (i.e. ex post-filtering using a two-sided Hodrick-Prescott filter with lambdas 10, 400, 1600) will make the signaling indicator gradually fully mononotic (above lambdas of 1500), i.e., there are no exceptions to the expected pattern of the stages and/or no jumps forth and back (displayed on the right hand): Quarters during which the signaling indicator increases between t-1 and t both in absolute terms and for the marginal change are called "expansion" stages – in addition to stages where the sign of the slope of the indicator changes (from negative to positive). Equivalent considerations lead to the three other stages (slowdown, contraction, recovery).[54]

Figure A. 3. The use of indices to determine the regimes (i.e., stages of the cycle)

Credit Index | Resulting stages



Source: Authors

However, shorter (sub)cycles are being gradually removed and, more importantly, the turning points for the downturns change by several quarters[55], which is undesirable and was found to

54 I.e., if the cycle is improving (i.e. the index upward sloping), but the marginal increase is lower than in the previous period, we would refer to a "slowdown" stage. Falling indicators characterize a "recession" (with a marginal drop or a change of the sign of the slope from positive to negative) or a "recovery" (marginal increase compared to previous period).

55 For the GFC, for example, the raw data suggest that the contraction stage begins in December 2008 (i.e., the index reaches a peak in September 2008), which also holds for a lambda of 10. For higher lambdas, the turning point is three/eleven quarters earlier (lambda 400/1600), a telling example of the phase-shift inherent in the HP filter (which can go into either direction).

result in inferior performance. Hence, we abstain from using filtered series for real time analysis.[56]

We construct the stages in three steps (see *Table A. 2*): first, we extract trends, using changes in the transformed series (*Table 1* and *Table A. 3*); second, we smooth the series, using an HP-filter for the in-sample analysis and exponentially[57] weighted moving averages for the out-of-sample analysis; third, we use a rule-of-thumb (see below) to reduce the number of stages for all series (including the growth-inflation regime). This approach substantially reduces the number of stages for the raw data, the number of stages is about 100 during the period from Q2/1980-Q4/2018 (i.e. 155 quarters), which means that the stages change every other quarter (and these changes include numerous inconsistencies in the sequence of the stages). After applying a rule of thumb (step 3, see below), the number of stages drops to about 20 stages in-sample and to around 40 out-of-sample, and 15-20 for the growth-inflation regime both in- and out-of-sample. An exception is the Economic Climate Index, for which the number of stages remains somewhat higher.

Table A. 2. Concept to establish stages

Element	In-sample analysis	Out-of-sample analysis
Step 1 (Trend extraction)	• Computation of medium-term (i.e., multi-year) trends (see *Table 1*), accounting for the nature of the metrics (e.g., growth rates (business cycles) vs. indices (financial cycles)), volatility and relationship with the original series (avoiding phase-shifts).	• Computation of medium-term (i.e., multi-year) trends (see Table *1*), accounting for the nature of the metrics (as for in-sample computation)
Step 2 (Smoothing of trends, see Figure A. 3)	• Smoothing of trends based on two-sided HP-filter	• Smoothing of series using exponentially weighted moving averages, based on the latest four or six observations[58], reflecting the properties of the raw signaling variables (more or less volatile) and depending on whether the transformed series lead the asset price cycles or not; • Other techniques considered: Locally weighted scatterplot smoothing (LOESS) did not turn out to be superior; Markow-switching not applied, given higher complexity.

56 The downside properties of the HP filter (phase-shifts, asymmetry of the cut-off region; see Nilsson and Gyomai (2011), for example) are well-known and alternative concepts (such as nested HP-filtering) were considered too complex for the purpose at hand.

57 The advantage of using an exponentially weighted average is that it puts high emphasis on the most recent data points, while still capturing trends.

58 Weights for 4 observations: 6% (t-4), 12.5% (t-3); 25% (t-2); and 56.5% (t-1); 6 observations: 5%, 9%, 14%, 19%, 24% and 29%)

Step 3 (Smoothing of stages)	• Use of a rule of thumb to establish stages that follow a more sequential manner (i.e., avoid fourth-and-back jumps of stages): count the occurrence of the four stages during the previous three quarters, and assign the stages based on the highest count. Assume, for example, that the last three observations (t, t-1, t-2) include three "expansion" phases, then we assign "expansion". If the next observation (t+1) were to be a "slowdown" phase, we would still assign "expansion" in t+1, and would only switch to "slowdown" in t+2 (if that phase was again a "slowdown" phase). In cases where the last three observations include three different stages (i.e. are at par), we assign the most recent stage. Note that similar approaches have been used by Smirnov (2011), for example.

Source: Authors

The raw series of the signaling indicators were transformed so as to maximize the out-of-sample performance (steps 1 and 2 in *Table A. 2*), by choosing a favorable trade-off between trending and smoothing the signaling indicators on the one hand (making them more monotonic associated with less frequent asset re-balancing, and aligning their trend more closely to the equity price cycles) and retaining relevant patterns in the raw data on the other (i.e. avoiding time shifts and the removal of less defined stages altogether).

Table A. 3 shows the time horizon used to extract trends (step 1), along with the lamdas used to smooth the in-sample series as well as the number of observations used to compute exponentially weighted moving averages out of sample (step 2). The table also shows the definition of the FSI used for the respective countries.

Table A. 3. Overview of specifications of signaling indicators in- and out-of-sample

Indicator	**DE**		**JP**		**GB**		**US**	
	in	**out**	**in**	**out**	**in**	**out**	**in**	**Out**
GDPI	5 (200)	5 (6)	2 (200)	2 (6)	5 (100)	5 (4)	3 (200)	3 (4)
ECI	1 (200)	1 (4)	2 (300)	2 (6)	2 (100)	2 (4)	5 (100)	5 (4)
G/I	3	3	4	4	5	5	5	5
CI	7 (100)	7 (4)	3 (100)	3 (6)	5 (100)	5 (4)	3 (200)	3 (6)
FSI	5 (200) LV	5 (6) LV	5 (300) LV	5 (6) LV	2 (300) LV & EP	2 (6) LV & EP	3 (300) LV & EP	3 (6) LV & EP

Source: Authors

Note: the table provides information on the transformation of the raw signaling indicators to extract trends (e.g. 5 years in case of the German GDPI), along with the lamdas used for in-sample HP filtering (e.g. 200 for the German GDPI) and the number of observations used to compute exponentially weighted moving averages out of sample (e.g. 6 for the German GDPI). For the FSI model, the table provides the underlying specification.

Legend: GDPI: GDP Index; ECI: Economic Climate Index; G/I: Growth/Inflation; CI: Credit Index; FSI: Financial Stability Index (see above for the definitions of "LV" and "LV & EP")

Step 3: Asset allocation rules

We considered asset allocation rules that explicitly account for the volatility of asset returns during the different stages. To this end, we applied mean-variance optimization for the each of the five concepts and each stage in the cycle. However, given fairly limited data points, especially for the initial period of the real time out-of-sample analysis, we decided to allocate assets based on a simpler approach, which yielded similar results.

Specifically, we used three metrics to establish a cut-off between assets to be included and excluded, respectively, for each asset class and stage: (i) the average total returns; (ii) the average total returns minus half of a standard deviation of the asset class specific returns; (iii) and a Sharpe ratio. The portfolio weights were then determined based on the contribution of each asset class to the sum of the excess returns of all asset classes above the cut-off point.[59]

Based on different cut-off points, we established three portfolios with an increasing level of concentration:

- A *balanced* portfolio (cut-off at 40th percentile of asset returns of all asset classes);
- A *moderately concentrated* portfolio (cut-off at 60th percentile); and
- A *concentrated* portfolio (cut-off at 80th percentile).

A key purpose for the use of different levels of portfolio diversification was to assess whether the framework is robust enough to allow for an increase in performance at higher concentration levels. Nevertheless, there is room to improve asset allocation beyond illustrative purposes.

[59] As an example, take five asset classes, with total returns of 1%, 3%, 5%, 7% and 9%. Two asset classes are above the median return (5%), one with an excess return of 2 percentage points and another one with 4 percentage points. The portfolio allocation would then be one third (2/(2+4)) for the former asset class and two thirds for the second asset class.

Appendix 2. Outcome of the analysis: Asset Allocation based on different specifications

Table A. 4 Asset allocation conditional on the stage of the cycle for the United States (see Figure 2) (balanced portfolio)

GDPI — In-sample

Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%	2%	14%	44%	0%	25%	16%	0%
Recovery	0%	51%	0%	0%	5%	2%	7%	35%
Expansion	0%	33%	0%	0%	43%	0%	3%	20%
Slowdown	0%	19%	0%	0%	65%	3%	3%	11%
Average allocation over time	**Gold**	**Real E**	**Cash**	**Commodities**	**Equities**	**Sov Bonds**	**Corp IG**	**Corp HY**
Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Avg Return	Quarterly returns (by 2018)							
contraction	-0.4%	0.9%	1.4%	2.5%	0.6%	1.8%	1.5%	0.5%
recovery	2.5%	5.2%	1.1%	1.6%	3.2%	3.0%	3.2%	4.5%
expansion	-0.3%	3.2%	1.1%	1.5%	3.7%	1.6%	1.7%	2.5%
slowdown	0.8%	2.3%	0.9%	0.1%	4.5%	1.5%	1.6%	1.9%
StDev	Quarterly returns (by 2018)							
contraction	8.0%	14.1%	0.9%	14.4%	11.0%	3.6%	2.9%	6.6%
recovery	9.5%	6.7%	1.3%	8.6%	7.3%	4.6%	4.0%	4.2%
expansion	6.9%	5.5%	0.9%	8.4%	5.0%	4.2%	3.4%	3.1%
slowdown	7.1%	6.8%	0.7%	10.8%	7.4%	3.3%	2.6%	2.6%

GDPI — Out-of-sample

Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%	59%	0%	0%	9%	0%	9%	23%
Recovery	0%	3%	6%	0%	0%	37%	23%	30%
Expansion	0%	4%	0%	1%	87%	6%	1%	0%
Slowdown	12%	22%	0%	0%	51%	0%	0%	15%
Average allocation over time	**Gold**	**Real E**	**Cash**	**Commodities**	**Equities**	**Sov Bonds**	**Corp IG**	**Corp HY**
Contraction	0%	50%	0%	4%	6%	3%	9%	30%
Recovery	0%	15%	7%	0%	0%	25%	21%	32%
Expansion	0%	1%	0%	11%	64%	14%	8%	2%
Slowdown	6%	12%	0%	22%	52%	2%	1%	6%
Avg Return	Quarterly returns (by 2018)							
contraction	1.8%	5.0%	0.8%	1.3%	2.3%	1.8%	2.3%	3.0%
recovery	0.1%	1.4%	1.5%	0.6%	0.8%	2.6%	2.1%	2.3%
expansion	-0.9%	2.1%	1.1%	1.9%	4.9%	2.1%	2.0%	1.8%
slowdown	2.1%	2.4%	1.2%	1.3%	3.3%	1.8%	1.7%	2.2%
StDev	Quarterly returns (by 2018)							
contraction	5.8%	10.6%	0.7%	11.8%	9.6%	3.2%	2.9%	4.9%
recovery	11.0%	11.9%	1.5%	12.9%	9.2%	5.0%	4.3%	6.2%
expansion	7.2%	6.5%	0.9%	9.9%	6.0%	4.0%	3.1%	3.1%
slowdown	7.7%	6.6%	0.7%	9.3%	7.2%	3.4%	2.8%	4.2%

ECI — In-sample

Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	2%	0%	12%	0%	7%	60%	20%	0%
Recovery	0%	66%	0%	3%	19%	0%	5%	7%
Expansion	0%	52%	0%	0%	21%	1%	2%	24%
Slowdown	0%	31%	0%	0%	52%	3%	2%	12%
Average allocation over time	**Gold**	**Real E**	**Cash**	**Commodities**	**Equities**	**Sov Bonds**	**Corp IG**	**Corp HY**
Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Avg Return	Quarterly returns (by 2018)							
contraction	1.1%	-0.9%	1.2%	1.0%	1.1%	1.8%	1.3%	1.0%
recovery	1.4%	4.5%	1.3%	2.8%	3.2%	2.3%	2.8%	2.9%
expansion	-0.1%	4.7%	0.9%	1.8%	3.1%	2.0%	2.1%	3.2%
slowdown	1.5%	4.0%	1.2%	-0.1%	5.4%	2.2%	2.1%	2.8%
StDev	Quarterly returns (by 2018)							
contraction	8.8%	11.6%	0.8%	13.8%	10.1%	4.0%	3.3%	6.5%
recovery	10.2%	10.4%	1.4%	11.6%	9.5%	4.3%	3.7%	5.2%
expansion	7.5%	5.7%	0.9%	8.0%	5.0%	3.8%	3.1%	3.1%
slowdown	6.4%	5.0%	0.7%	8.6%	6.0%	4.0%	3.2%	2.6%

ECI — Out-of-sample

Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%	54%	0%	0%	11%	9%	7%	19%
Recovery	1%	22%	0%	44%	31%	0%	0%	1%
Expansion	0%	23%	0%	41%	27%	0%	1%	9%
Slowdown	0%	4%	0%	0%	40%	24%	13%	20%
Average allocation over time	**Gold**	**Real E**	**Cash**	**Commodities**	**Equities**	**Sov Bonds**	**Corp IG**	**Corp HY**
Contraction	0%	47%	0%	0%	28%	4%	5%	16%
Recovery	1%	11%	0%	51%	30%	2%	4%	0%
Expansion	0%	12%	1%	53%	20%	0%	2%	12%
Slowdown	0%	6%	0%	0%	38%	23%	12%	21%
Avg Return	Quarterly returns (by 2018)							
contraction	0.0%	3.3%	1.3%	-1.1%	2.3%	2.2%	2.2%	2.4%
recovery	2.6%	3.5%	0.9%	4.5%	3.9%	1.9%	2.3%	2.6%
expansion	0.5%	2.6%	1.0%	3.4%	2.8%	1.4%	1.5%	1.9%
slowdown	1.2%	2.0%	1.2%	-0.4%	3.5%	2.8%	2.4%	2.6%
StDev	Quarterly returns (by 2018)							
contraction	9.9%	12.7%	1.2%	14.0%	10.4%	4.1%	3.6%	6.2%
recovery	7.4%	7.8%	0.9%	8.4%	7.0%	3.5%	3.1%	4.1%
expansion	7.0%	6.3%	0.8%	8.8%	7.5%	3.2%	2.8%	3.2%
slowdown	6.0%	6.9%	0.8%	9.0%	6.1%	4.5%	3.4%	4.0%

CI

In-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	5%	18%	0%	39%	28%	0%	0%	10%
Recovery	0%	39%	0%	0%	39%	2%	3%	16%
Expansion	0%	20%	0%	0%	56%	6%	4%	14%
Slowdown	0%	7%	2%	74%	0%	5%	11%	0%
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Avg Return	Quarterly returns (by 2018)							
contraction	2.5%	2.8%	0.9%	3.3%	3.1%	1.9%	1.8%	2.6%
recovery	1.1%	3.6%	0.6%	-0.5%	3.6%	1.7%	1.8%	2.4%
expansion	0.0%	3.1%	1.2%	-1.3%	4.9%	2.4%	2.3%	2.7%
slowdown	-1.0%	1.9%	1.7%	4.3%	-0.3%	1.8%	2.0%	1.3%
StDev	Quarterly returns (by 2018)							
contraction	6.9%	13.9%	0.8%	14.2%	10.3%	3.4%	3.0%	6.2%
recovery	7.5%	6.0%	0.6%	6.6%	4.9%	3.3%	2.8%	2.6%
expansion	8.4%	6.7%	1.0%	9.6%	6.9%	4.3%	3.5%	3.8%
slowdown	8.9%	6.2%	1.1%	10.1%	8.4%	4.6%	3.9%	4.8%

Out-of-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%	54%	0%	0%	24%	0%	12%	10%
Recovery	0%	48%	0%	0%	15%	3%	5%	30%
Expansion	1%	0%	1%	0%	45%	36%	18%	0%
Slowdown	0%	8%	0%	31%	47%	0%	0%	13%
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%	28%	3%	4%	10%	20%	31%	5%
Recovery	0%	46%	0%	0%	5%	7%	6%	36%
Expansion	3%	0%	1%	19%	47%	19%	9%	1%
Slowdown	0%	27%	0%	17%	36%	0%	1%	19%
Avg Return	Quarterly returns (by 2018)							
contraction	0.9%	3.9%	1.6%	2.2%	3.0%	2.2%	2.6%	2.5%
recovery	1.4%	5.3%	0.8%	1.1%	3.1%	2.3%	2.5%	4.1%
expansion	1.0%	0.1%	1.0%	0.1%	2.5%	2.2%	1.6%	0.8%
slowdown	-1.1%	1.4%	1.0%	2.6%	3.5%	0.9%	0.9%	1.7%
StDev	Quarterly returns (by 2018)							
contraction	10.0%	9.9%	1.3%	11.1%	8.6%	4.5%	3.7%	5.0%
recovery	7.4%	6.0%	0.8%	8.4%	6.2%	3.7%	3.0%	3.4%
expansion	6.9%	10.8%	0.7%	13.0%	10.3%	3.8%	3.2%	5.3%
slowdown	6.0%	7.0%	0.5%	10.7%	5.7%	2.6%	2.0%	3.2%

FSI

In-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%	0%	2%	55%	23%	17%	4%	0%
Recovery	2%	59%	0%	9%	0%	0%	9%	21%
Expansion	0%	44%	0%	0%	29%	0%	4%	24%
Slowdown	0%	30%	0%	0%	48%	12%	5%	5%
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Avg Return	Quarterly returns (by 2018)							
contraction	0.7%	-0.8%	1.2%	3.3%	2.0%	1.8%	1.3%	0.9%
recovery	2.1%	4.1%	0.7%	2.3%	1.7%	1.6%	2.3%	2.8%
expansion	0.2%	4.3%	1.4%	1.8%	3.4%	1.9%	2.1%	3.2%
slowdown	0.1%	3.6%	1.1%	-2.1%	4.5%	2.6%	2.3%	2.3%
StDev	Quarterly returns (by 2018)							
contraction	7.4%	11.5%	0.7%	12.9%	10.3%	3.4%	2.9%	5.9%
recovery	6.5%	11.1%	0.7%	13.2%	9.9%	2.8%	2.5%	5.2%
expansion	9.2%	6.3%	1.3%	7.2%	6.1%	4.8%	4.1%	4.0%
slowdown	8.0%	6.3%	0.9%	10.3%	6.0%	3.9%	3.1%	2.9%

Out-of-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	3%	0%	0%	76%	18%	0%	0%	3%
Recovery	0%	49%	0%	0%	4%	9%	12%	25%
Expansion	0%	25%	0%	0%	44%	13%	6%	11%
Slowdown	0%	12%	0%	5%	78%	1%	0%	4%
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	1%	0%	1%	74%	18%	0%	2%	3%
Recovery	0%	41%	0%	0%	3%	11%	13%	32%
Expansion	0%	9%	0%	0%	44%	24%	14%	9%
Slowdown	8%	15%	0%	16%	56%	5%	0%	0%
Avg Return	Quarterly returns (by 2018)							
contraction	1.5%	1.0%	1.2%	5.8%	2.4%	1.2%	1.3%	1.4%
recovery	0.7%	4.1%	0.7%	-0.9%	1.7%	2.0%	2.2%	2.8%
expansion	0.0%	3.2%	1.4%	-0.3%	3.8%	2.7%	2.5%	2.7%
slowdown	1.6%	2.5%	1.3%	2.2%	5.2%	2.1%	1.9%	2.2%
StDev	Quarterly returns (by 2018)							
contraction	7.3%	7.7%	0.7%	8.3%	8.1%	3.5%	3.1%	4.0%
recovery	5.9%	12.8%	0.7%	14.0%	10.4%	3.2%	3.0%	6.3%
expansion	9.6%	6.1%	1.3%	9.4%	6.2%	4.6%	3.6%	3.5%
slowdown	9.4%	5.9%	0.7%	7.1%	5.2%	4.1%	3.2%	2.6%

G/I	In-sample								
	Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
	ng_ni	0%	43%	0%	0%	36%	0%	3%	17%
	ng_i	0%	43%	0%	0%	3%	13%	11%	30%
	g_ni	0%	20%	0%	78%	1%	0%	1%	0%
	g_i	0%	1%	0%	25%	66%	6%	3%	0%
	Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
	Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Avg Return								
	ng_ni	1.1%	3.5%	0.1%	0.2%	3.1%	1.0%	1.2%	2.0%
	ng_i	-0.2%	4.0%	1.9%	-1.3%	2.4%	2.9%	2.8%	3.5%
	g_ni	1.3%	2.0%	1.2%	4.0%	1.3%	1.2%	1.3%	1.2%
	g_i	1.3%	2.3%	1.5%	3.0%	4.1%	2.5%	2.4%	2.2%
	StDev	Quarterly returns (by 2018)							
	ng_ni	7.8%	6.2%	0.2%	11.1%	6.4%	2.9%	2.6%	3.0%
	ng_i	11.9%	14.9%	1.4%	13.4%	11.2%	6.1%	5.0%	7.8%
	g_ni	5.1%	8.6%	0.4%	11.0%	8.3%	3.0%	2.7%	4.8%
	g_i	7.2%	6.2%	0.5%	8.6%	7.1%	3.7%	2.9%	3.8%

Out-of-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
ng_ni	0%	61%	0%	6%	7%	0%	0%	25%
ng_i	0%	21%	0%	0%	1%	27%	22%	29%
g_ni	0%	10%	0%	0%	71%	8%	7%	4%
g_i	19%	43%	0%	1%	36%	0%	0%	2%
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
ng_ni	0%	41%	0%	7%	8%	6%	7%	31%
ng_i	0%	15%	3%	3%	1%	28%	22%	28%
g_ni	0%	3%	0%	20%	61%	7%	4%	5%
g_i	30%	38%	2%	5%	25%	0%	0%	1%
Avg Return	Quarterly returns (by 2018)							
ng_ni	1.3%	4.0%	0.9%	2.5%	2.5%	2.3%	2.3%	3.0%
ng_i	1.3%	2.6%	1.5%	0.6%	1.6%	2.9%	2.6%	2.9%
g_ni	0.1%	2.0%	1.2%	1.2%	3.6%	1.9%	1.9%	1.8%
g_i	3.2%	5.5%	1.2%	1.5%	4.8%	0.0%	0.8%	1.6%
StDev	Quarterly returns (by 2018)							
ng_ni	6.0%	5.8%	0.9%	8.8%	5.6%	4.0%	3.3%	3.3%
ng_i	11.6%	16.5%	1.5%	15.1%	12.5%	4.9%	4.4%	7.5%
g_ni	6.7%	6.6%	0.7%	10.5%	7.7%	3.4%	2.7%	4.0%
g_i	12.5%	6.3%	1.2%	7.9%	5.2%	5.4%	4.2%	6.4%

Source: Authors

Table A. 5 Performance metrics for out-of-sample asset allocation for the US

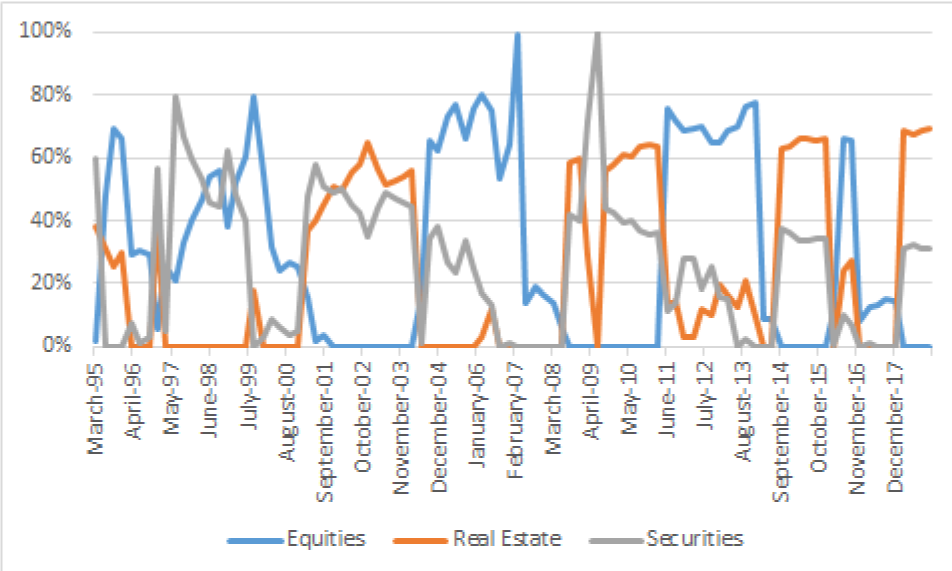
Balanced PF	FSI	CI	GDPI	ECI	GI	60/40	Equity only	Rf
Avg	0.14	0.11	0.10	0.12	0.10	0.10	0.15	0.07
StDev	0.22	0.21	0.25	0.29	0.20	0.20	0.37	0.13
Sharpe	0.34	0.20	0.15	0.18	0.18	0.16	0.23	0.00
Avg	0.13	0.09	0.09	0.11	0.08	0.07	0.11	0.06
StDev	0.24	0.21	0.26	0.32	0.19	0.20	0.39	0.12
Sharpe	0.31	0.15	0.11	0.16	0.11	0.06	0.14	0.00
Avg	0.12	0.11	0.13	0.13	0.09	0.12	0.20	0.04
StDev	0.21	0.20	0.30	0.36	0.19	0.21	0.44	0.11
Sharpe	0.39	0.37	0.31	0.25	0.29	0.36	0.37	0.00
Mod conc PF	FSI	CI	GDPI	ECI	GI	60/40	Equity only	Rf
Avg	0.16	0.12	0.12	0.14	0.11	0.10	0.15	0.07
StDev	0.24	0.23	0.29	0.40	0.22	0.20	0.37	0.13
Sharpe	0.36	0.24	0.17	0.19	0.22	0.16	0.23	0.00
Avg	0.15	0.10	0.10	0.13	0.09	0.07	0.11	0.06
StDev	0.26	0.23	0.31	0.44	0.20	0.20	0.39	0.12
Sharpe	0.33	0.18	0.13	0.16	0.15	0.06	0.14	0.00
Avg	0.13	0.12	0.16	0.16	0.10	0.12	0.20	0.04
StDev	0.22	0.22	0.36	0.54	0.20	0.21	0.44	0.11
Sharpe	0.43	0.38	0.33	0.23	0.31	0.36	0.37	0.00
Concentrated PF	FSI	CI	GDPI	ECI	GI	60/40	Equity only	Rf
Avg	0.19	0.13	0.14	0.16	0.13	0.10	0.15	0.07
StDev	0.28	0.26	0.33	0.49	0.23	0.20	0.37	0.13
Sharpe	0.42	0.25	0.23	0.19	0.27	0.16	0.23	0.00
Avg	0.18	0.10	0.12	0.16	0.11	0.07	0.11	0.06
StDev	0.30	0.25	0.35	0.53	0.22	0.20	0.39	0.12
Sharpe	0.40	0.17	0.18	0.19	0.21	0.06	0.14	0.00
Avg	0.17	0.13	0.19	0.18	0.11	0.12	0.20	0.04
StDev	0.26	0.23	0.41	0.65	0.22	0.21	0.44	0.11
Sharpe	0.50	0.41	0.36	0.22	0.35	0.36	0.37	0.00

Note: The table shows metrics for annualised quarterly total returns[60]; "Rf": Risk-free rate of total returns (100% investment in sovereign bonds); for a definition of the risk allocation strategies (i.e. the meaning of the cut-off values see section V.B).

Source: Authors

[60] i.e. a quarterly total return of 2.5% would enter the computation as 10.3%.

Figure A. 4: US: Out-of-sample asset allocation for FSI over time



Note: Securities include government bonds and corporate bonds (both IG and HY). Figures are for moderately concentrated portfolio.

Source: Authors

Table A. 6 Asset allocation conditional on the stage of the cycle for Germany (balanced portfolio)

GDPI — In-sample

Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		0%	53%	36%	11%		
Recovery	0%		0%	1%	73%	26%		
Expansion	6%		0%	33%	61%	0%		
Slowdown	4%		41%	0%	0%	55%		
Average allocation over time	**Gold**	**Real E**	**Cash**	**Commodities**	**Equities**	**Sov Bonds**	**Corp IG**	**Corp HY**
Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Avg Return	**Quarterly returns (by 2018)**							
contraction	1.4%		1.3%	2.6%	2.3%	1.9%		
recovery	0.0%		0.8%	0.9%	5.7%	2.6%		
expansion	1.5%		0.8%	2.4%	3.3%	1.0%		
slowdown	-0.2%		1.0%	-0.6%	-0.8%	1.5%		
StDev	**Quarterly returns (by 2018)**							
contraction	9.9%		0.9%	7.8%	10.1%	3.2%		
recovery	6.1%		0.4%	9.7%	10.7%	3.0%		
expansion	8.5%		0.5%	10.8%	10.5%	2.9%		
slowdown	6.7%		1.0%	14.5%	11.8%	3.1%		

GDPI — Out-of-sample

Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		0%	19%	79%	2%		
Recovery	0%		3%	0%	67%	30%		
Expansion	28%		22%	0%	0%	50%		
Slowdown	31%		0%	64%	0%	4%		
Average allocation over time	**Gold**	**Real E**	**Cash**	**Commodities**	**Equities**	**Sov Bonds**	**Corp IG**	**Corp HY**
Contraction	1%		9%	34%	51%	5%		
Recovery	0%		7%	5%	61%	27%		
Expansion	13%		11%	34%	25%	18%		
Slowdown	4%		9%	43%	31%	12%		
Avg Return	**Quarterly returns (by 2018)**							
contraction	-0.4%		1.0%	1.7%	3.8%	1.1%		
recovery	0.3%		0.8%	0.4%	5.3%	2.7%		
expansion	1.1%		1.0%	-0.4%	-0.1%	1.5%		
slowdown	2.7%		1.2%	3.7%	1.5%	1.9%		
StDev	**Quarterly returns (by 2018)**							
contraction	9.9%		0.9%	8.1%	7.9%	3.0%		
recovery	4.9%		0.5%	9.6%	8.4%	2.8%		
expansion	7.9%		0.7%	13.9%	12.9%	3.4%		
slowdown	6.9%		0.8%	11.9%	13.9%	2.8%		

ECI — In-sample

Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		0%	41%	59%	0%		
Recovery	0%		12%	0%	42%	46%		
Expansion	46%		0%	0%	13%	41%		
Slowdown	0%		0%	76%	13%	11%		
Average allocation over time	**Gold**	**Real E**	**Cash**	**Commodities**	**Equities**	**Sov Bonds**	**Corp IG**	**Corp HY**
Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Avg Return	**Quarterly returns (by 2018)**							
contraction	0.7%		1.0%	3.8%	5.1%	1.1%		
recovery	0.3%		1.2%	-1.6%	2.0%	2.1%		
expansion	2.4%		1.0%	0.1%	1.7%	2.2%		
slowdown	0.4%		0.7%	3.7%	1.7%	1.6%		
StDev	**Quarterly returns (by 2018)**							
contraction	6.6%		0.5%	9.6%	10.4%	3.0%		
recovery	10.3%		0.8%	12.6%	11.6%	3.7%		
expansion	9.7%		1.0%	11.5%	12.3%	3.0%		
slowdown	5.4%		0.6%	8.4%	8.3%	3.2%		

ECI — Out-of-sample

Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	8%		0%	0%	75%	17%		
Recovery	0%		3%	69%	0%	28%		
Expansion	0%		0%	53%	38%	9%		
Slowdown	12%		0%	0%	76%	12%		
Average allocation over time	**Gold**	**Real E**	**Cash**	**Commodities**	**Equities**	**Sov Bonds**	**Corp IG**	**Corp HY**
Contraction	5%		5%	30%	37%	23%		
Recovery	9%		1%	23%	57%	10%		
Expansion	4%		2%	16%	66%	12%		
Slowdown	5%		4%	32%	45%	15%		
Avg Return	**Quarterly returns (by 2018)**							
contraction	1.4%		1.0%	-0.5%	2.8%	1.6%		
recovery	0.8%		1.1%	3.3%	0.9%	2.0%		
expansion	-1.0%		0.8%	2.9%	2.4%	1.5%		
slowdown	2.0%		0.9%	1.0%	4.2%	2.0%		
StDev	**Quarterly returns (by 2018)**							
contraction	7.7%		0.7%	13.8%	11.7%	3.5%		
recovery	7.4%		0.9%	10.2%	15.2%	3.0%		
expansion	7.3%		0.7%	8.1%	7.2%	2.5%		
slowdown	9.4%		0.6%	8.4%	9.5%	3.0%		

CI — In-sample

Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	15%		0%	82%	0%	3%		
Recovery	18%		0%	70%	12%	0%		
Expansion	2%		0%	0%	63%	35%		
Slowdown	0%		10%	0%	61%	29%		
Average allocation over time	**Gold**	**Real E**	**Cash**	**Commodities**	**Equities**	**Sov Bonds**	**Corp IG**	**Corp HY**
Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Avg Return	**Quarterly returns (by 2018)**							
contraction	2.1%		1.0%	4.1%	1.5%	1.7%		
recovery	2.1%		1.1%	3.4%	1.9%	0.9%		
expansion	1.1%		1.0%	-0.2%	2.4%	1.8%		
slowdown	-1.3%		0.9%	-0.5%	4.0%	2.1%		
StDev	**Quarterly returns (by 2018)**							
contraction	6.8%		0.3%	10.0%	14.4%	2.9%		
recovery	7.7%		0.5%	14.6%	10.8%	3.5%		
expansion	7.4%		1.0%	11.4%	9.9%	3.1%		
slowdown	9.1%		0.9%	8.2%	8.7%	2.9%		

CI — Out-of-sample

Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	28%		0%	68%	0%	4%		
Recovery	10%		0%	37%	53%	0%		
Expansion	0%		12%	0%	52%	36%		
Slowdown	0%		3%	0%	70%	27%		
Average allocation over time	**Gold**	**Real E**	**Cash**	**Commodities**	**Equities**	**Sov Bonds**	**Corp IG**	**Corp HY**
Contraction	5%		4%	62%	24%	5%		
Recovery	3%		3%	65%	30%	0%		
Expansion	0%		17%	0%	51%	32%		
Slowdown	1%		10%	0%	61%	28%		
Avg Return	**Quarterly returns (by 2018)**							
contraction	2.3%		0.8%	4.1%	0.3%	1.2%		
recovery	1.8%		1.2%	2.5%	3.0%	0.7%		
expansion	-0.7%		1.1%	-0.7%	3.4%	2.4%		
slowdown	0.2%		0.8%	-0.6%	5.7%	2.6%		
StDev	**Quarterly returns (by 2018)**							
contraction	7.1%		0.5%	10.3%	10.8%	2.3%		
recovery	6.5%		0.5%	15.6%	13.2%	3.4%		
expansion	8.9%		0.9%	8.9%	10.4%	3.1%		
slowdown	8.6%		0.8%	5.9%	7.1%	3.1%		

FSI — In-sample

Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	24%		0%	69%	0%	7%		
Recovery	0%		1%	64%	35%	0%		
Expansion	0%		4%	0%	73%	22%		
Slowdown	1%		0%	0%	57%	42%		
Average allocation over time	**Gold**	**Real E**	**Cash**	**Commodities**	**Equities**	**Sov Bonds**	**Corp IG**	**Corp HY**
Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Avg Return	**Quarterly returns (by 2018)**							
contraction	2.1%		0.7%	3.9%	-0.5%	1.5%		
recovery	-0.6%		1.1%	3.5%	2.4%	1.0%		
expansion	0.3%		1.2%	0.4%	5.7%	2.3%		
slowdown	1.0%		0.9%	-1.5%	2.1%	1.8%		
StDev	**Quarterly returns (by 2018)**							
contraction	7.6%		0.4%	11.8%	13.1%	2.5%		
recovery	8.6%		1.0%	9.0%	11.2%	3.4%		
expansion	9.2%		0.8%	8.3%	7.6%	2.5%		
slowdown	6.2%		0.5%	13.3%	11.3%	3.6%		

FSI — Out-of-sample

Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		0%	84%	0%	15%		
Recovery	1%		0%	81%	18%	0%		
Expansion	0%		19%	0%	45%	37%		
Slowdown	0%		0%	0%	87%	13%		
Average allocation over time	**Gold**	**Real E**	**Cash**	**Commodities**	**Equities**	**Sov Bonds**	**Corp IG**	**Corp HY**
Contraction	13%		1%	71%	4%	12%		
Recovery	2%		9%	73%	16%	0%		
Expansion	0%		16%	0%	56%	27%		
Slowdown	0%		3%	2%	80%	16%		
Avg Return	**Quarterly returns (by 2018)**							
contraction	1.4%		0.9%	4.6%	1.4%	2.0%		
recovery	1.6%		1.0%	4.3%	2.2%	1.6%		
expansion	-0.3%		1.1%	-3.3%	1.9%	1.6%		
slowdown	0.7%		0.9%	0.9%	6.6%	1.8%		
StDev	**Quarterly returns (by 2018)**							
contraction	10.6%		0.7%	8.1%	10.2%	2.4%		
recovery	6.2%		0.7%	7.5%	13.2%	3.4%		
expansion	6.7%		0.8%	12.8%	10.6%	3.3%		
slowdown	7.6%		0.7%	12.0%	8.7%	3.1%		

G/I	In-sample								
	Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
	ng_ni	13%		0%	24%	63%	0%		
	ng_i	0%		6%	0%	67%	27%		
	g_ni	0%		6%	92%	0%	2%		
	g_i	6%		3%	0%	0%	91%		
	Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
	Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Avg Return								
	ng_ni	2.0%		0.5%	2.2%	3.3%	1.0%		
	ng_i	-1.3%		1.0%	-0.4%	6.6%	2.9%		
	g_ni	0.6%		0.9%	3.5%	-1.1%	0.8%		
	g_i	1.8%		1.8%	-0.1%	1.7%	2.6%		
	StDev	Quarterly returns (by 2018)							
	ng_ni	6.2%		0.4%	10.4%	10.6%	3.2%		
	ng_i	5.1%		0.5%	8.6%	8.1%	2.4%		
	g_ni	8.3%		0.6%	10.7%	13.9%	2.6%		
	g_i	12.0%		0.9%	12.9%	8.5%	3.9%		

Out-of-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
ng_ni	0%		6%	0%	69%	25%		
ng_i	0%		0%	41%	59%	0%		
g_ni	0%		3%	92%	0%	6%		
g_i	22%		0%	0%	37%	41%		
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
ng_ni	0%		6%	10%	69%	16%		
ng_i	3%		0%	12%	72%	14%		
g_ni	32%		6%	39%	25%	2%		
g_i	37%		2%	1%	8%	53%		
Avg Return	Quarterly returns (by 2018)							
ng_ni	0.0%		1.0%	0.3%	4.0%	1.9%		
ng_i	1.9%		1.1%	3.7%	4.5%	1.9%		
g_ni	0.8%		1.0%	3.9%	-0.3%	1.1%		
g_i	2.0%		0.9%	-1.3%	2.2%	2.3%		
StDev	Quarterly returns (by 2018)							
ng_ni	7.4%		0.8%	10.3%	10.8%	3.1%		
ng_i	9.8%		0.6%	6.5%	7.2%	3.2%		
g_ni	7.7%		0.8%	9.4%	12.7%	2.5%		
g_i	9.6%		0.9%	14.8%	9.9%	4.2%		

Source: Authors

Table A. 7 Performance metrics for out-of-sample asset allocation for Germany

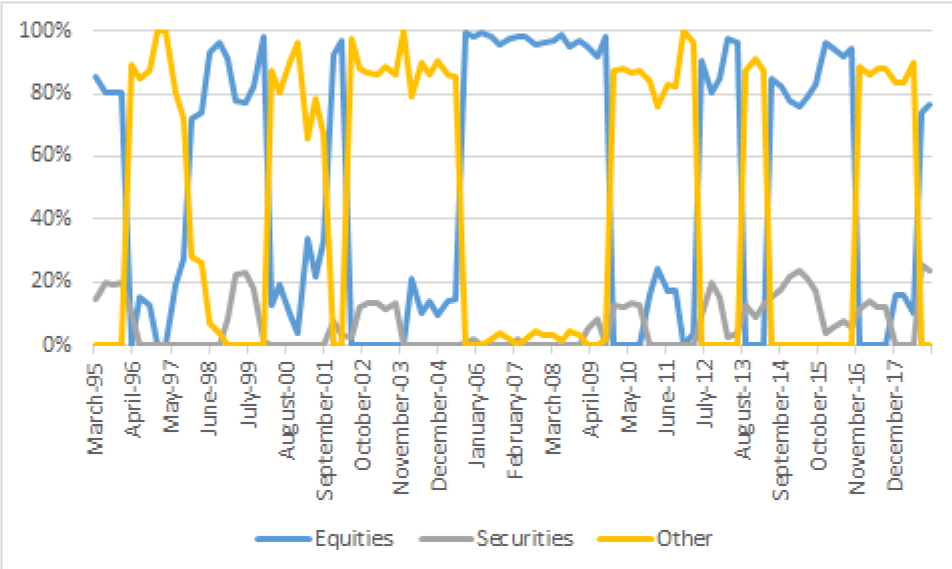
OOS	Balanced PF	FSI	CI	GDPI	ECI	GI	60/40	Equity only	Rf
1995-2018	Avg	0.14	0.13	0.12	0.12	0.13	0.11	0.18	0.07
1995-2018	StDev	0.32	0.35	0.36	0.34	0.33	0.28	0.49	0.13
1995-2018	Sharpe	0.22	0.17	0.12	0.14	0.19	0.13	0.23	0.00
2000-2018	Avg	0.13	0.12	0.09	0.11	0.11	0.08	0.13	0.07
2000-2018	StDev	0.31	0.37	0.37	0.36	0.34	0.26	0.47	0.13
2000-2018	Sharpe	0.19	0.14	0.07	0.11	0.13	0.04	0.14	0.00
2009-2018	Avg	0.11	0.09	0.10	0.09	0.08	0.10	0.16	0.06
2009-2018	StDev	0.29	0.27	0.40	0.32	0.33	0.23	0.41	0.13
2009-2018	Sharpe	0.17	0.11	0.11	0.09	0.06	0.17	0.26	0.00
OOS	**Mod conc PF**	FSI	CI	GDPI	ECI	GI	60/40	Equity only	Rf
1995-2018	Avg	0.19	0.15	0.14	0.15	0.16	0.11	0.18	0.07
1995-2018	StDev	0.41	0.41	0.41	0.41	0.40	0.28	0.49	0.13
1995-2018	Sharpe	0.28	0.20	0.16	0.19	0.23	0.13	0.23	0.00
2000-2018	Avg	0.16	0.13	0.11	0.13	0.13	0.08	0.13	0.07
2000-2018	StDev	0.39	0.43	0.42	0.42	0.39	0.26	0.47	0.13
2000-2018	Sharpe	0.25	0.16	0.10	0.16	0.16	0.04	0.14	0.00
2009-2018	Avg	0.13	0.11	0.12	0.11	0.08	0.10	0.16	0.06
2009-2018	StDev	0.34	0.33	0.46	0.39	0.37	0.23	0.41	0.13
2009-2018	Sharpe	0.20	0.15	0.14	0.13	0.07	0.17	0.26	0.00
OOS	**Concentrated PF**	FSI	CI	GDPI	ECI	GI	60/40	Equity only	Rf
1995-2018	Avg	0.22	0.19	0.17	0.17	0.19	0.11	0.18	0.07
1995-2018	StDev	0.46	0.50	0.48	0.46	0.46	0.28	0.49	0.13
1995-2018	Sharpe	0.32	0.23	0.20	0.21	0.26	0.13	0.23	0.00
2000-2018	Avg	0.19	0.16	0.14	0.14	0.15	0.08	0.13	0.07
2000-2018	StDev	0.43	0.50	0.48	0.47	0.44	0.26	0.47	0.13
2000-2018	Sharpe	0.29	0.18	0.15	0.17	0.19	0.04	0.14	0.00
2009-2018	Avg	0.15	0.16	0.15	0.11	0.10	0.10	0.16	0.06
2009-2018	StDev	0.39	0.44	0.50	0.43	0.42	0.23	0.41	0.13
2009-2018	Sharpe	0.24	0.24	0.18	0.12	0.09	0.17	0.26	0.00

Note: The table shows metrics for annualised quarterly total returns[61]; "Rf": Risk-free rate of total returns (100% investment in sovereign bonds); for a definition of the risk allocation strategies (i.e. the meaning of the cut-off values see section V.B).

Source: Authors

[61] i.e. a quarterly total return of 2.5% would enter the computation as 10.3%.

Figure A. 5: DE: Out-of-sample asset allocation for FSI over time



Note: Securities include government bonds. Figures are for moderately concentrated portfolio.

Source: Authors

Table A. 8 Asset allocation conditional on the stage of the cycle for Japan (balanced portfolio)

GDPI	In-sample							
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	58%		14%	28%	0%	0%	0%	
Recovery	6%		9%	86%	0%	0%	0%	
Expansion	0%		14%	0%	52%	34%	0%	
Slowdown	0%		5%	0%	73%	22%	0%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Avg Return	Quarterly returns (by 2018)							
contraction	2.0%		0.9%	1.3%	-0.4%	0.6%	0.2%	
recovery	1.4%		1.4%	3.6%	1.0%	1.2%	0.4%	
expansion	-0.2%		1.0%	0.4%	2.6%	1.8%	0.4%	
slowdown	-0.6%		0.7%	0.4%	3.3%	1.3%	0.5%	
StDev	Quarterly returns (by 2018)							
contraction	7.2%		0.7%	13.7%	11.7%	2.8%	0.6%	
recovery	10.7%		1.0%	10.4%	7.8%	2.3%	0.7%	
expansion	6.1%		0.6%	6.6%	9.7%	3.0%	0.3%	
slowdown	7.3%		0.5%	10.1%	9.5%	3.7%	0.9%	

GDPI	Out-of-sample							
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	34%		19%	0%	0%	48%	0%	
Recovery	52%		7%	0%	40%	0%	0%	
Expansion	0%		13%	15%	71%	0%	0%	
Slowdown	0%		0%	54%	42%	4%	0%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	4%		31%	3%	6%	52%	4%	
Recovery	6%		17%	6%	62%	9%	0%	
Expansion	0%		11%	39%	47%	4%	0%	
Slowdown	0%		4%	55%	38%	3%	0%	
Avg Return	Quarterly returns (by 2018)							
contraction	1.3%		0.9%	-0.2%	-1.3%	1.6%	0.5%	
recovery	2.4%		1.4%	-0.3%	2.1%	1.3%	0.2%	
expansion	0.1%		0.9%	0.9%	2.1%	0.6%	0.3%	
slowdown	-0.3%		0.8%	5.6%	4.6%	1.2%	0.5%	
StDev	Quarterly returns (by 2018)							
contraction	6.8%		0.7%	13.8%	11.3%	2.8%	0.7%	
recovery	10.9%		1.0%	8.2%	8.1%	2.3%	0.6%	
expansion	6.4%		0.5%	9.6%	8.6%	3.8%	0.8%	
slowdown	8.4%		0.6%	9.0%	10.4%	2.7%	0.6%	

ECI	In-sample							
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	9%		0%	2%	89%	0%	0%	
Recovery	0%		30%	56%	0%	14%	0%	
Expansion	66%		12%	0%	0%	22%	0%	
Slowdown	0%		0%	18%	69%	13%	0%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Avg Return	Quarterly returns (by 2018)							
contraction	1.5%		0.8%	1.3%	4.0%	1.2%	0.3%	
recovery	0.4%		1.1%	1.6%	0.0%	0.7%	0.4%	
expansion	2.3%		1.4%	1.2%	-0.7%	1.6%	0.5%	
slowdown	0.0%		0.8%	1.5%	3.2%	1.3%	0.3%	
StDev	Quarterly returns (by 2018)							
contraction	6.6%		0.5%	10.3%	9.2%	3.7%	0.5%	
recovery	9.5%		0.8%	14.9%	11.6%	3.1%	1.0%	
expansion	9.7%		0.9%	8.4%	8.4%	2.3%	0.6%	
slowdown	7.2%		0.6%	7.8%	9.0%	2.8%	0.5%	

ECI	Out-of-sample							
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	31%		0%	0%	59%	10%	0%	
Recovery	0%		0%	77%	19%	4%	0%	
Expansion	0%		8%	72%	0%	20%	0%	
Slowdown	0%		20%	0%	60%	19%	0%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	4%		6%	38%	44%	8%	0%	
Recovery	1%		16%	58%	6%	19%	0%	
Expansion	0%		24%	21%	32%	23%	0%	
Slowdown	0%		8%	17%	68%	7%	0%	
Avg Return	Quarterly returns (by 2018)							
contraction	1.6%		0.9%	0.4%	2.2%	1.1%	0.4%	
recovery	0.3%		0.9%	5.9%	2.1%	1.1%	0.4%	
expansion	0.9%		1.1%	2.5%	-0.1%	1.3%	0.5%	
slowdown	0.0%		1.0%	-2.8%	2.6%	1.0%	0.2%	
StDev	Quarterly returns (by 2018)							
contraction	5.9%		0.7%	14.1%	11.1%	3.0%	0.7%	
recovery	9.3%		0.8%	9.6%	10.6%	3.3%	0.5%	
expansion	9.8%		0.9%	8.4%	9.7%	2.9%	0.7%	
slowdown	6.4%		0.6%	9.0%	8.0%	3.2%	0.9%	

CI

In-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		26%	0%	43%	31%	0%	
Recovery	0%		18%	0%	0%	69%	14%	
Expansion	3%		26%	71%	0%	0%	0%	
Slowdown	23%		0%	37%	41%	0%	0%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Avg Return	Quarterly returns (by 2018)							
contraction	-0.6%		1.2%	-0.1%	1.8%	1.4%	0.4%	
recovery	-0.7%		0.6%	0.2%	-0.3%	1.6%	0.5%	
expansion	1.1%		1.2%	1.6%	1.0%	0.8%	0.3%	
slowdown	2.1%		0.9%	2.8%	3.0%	1.1%	0.4%	
StDev	Quarterly returns (by 2018)							
contraction	7.8%		1.0%	9.2%	11.8%	3.7%	0.2%	
recovery	5.4%		0.6%	8.6%	9.5%	2.4%	0.7%	
expansion	10.0%		0.7%	13.1%	10.2%	2.2%	1.0%	
slowdown	7.6%		0.5%	11.2%	8.7%	3.5%	0.6%	

Out-of-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		16%	0%	75%	9%	0%	
Recovery	33%		0%	42%	0%	25%	0%	
Expansion	50%		19%	0%	0%	31%	0%	
Slowdown	11%		0%	77%	0%	12%	0%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		7%	46%	28%	19%	0%	
Recovery	13%		0%	29%	2%	28%	28%	
Expansion	11%		14%	23%	34%	18%	0%	
Slowdown	0%		4%	45%	25%	27%	0%	
Avg Return	Quarterly returns (by 2018)							
contraction	-0.7%		1.2%	0.5%	3.7%	0.9%	0.2%	
recovery	1.7%		0.9%	1.9%	0.8%	1.5%	0.5%	
expansion	1.3%		0.9%	0.3%	0.7%	1.1%	0.5%	
slowdown	1.4%		0.8%	5.0%	0.3%	1.4%	0.3%	
StDev	Quarterly returns (by 2018)							
contraction	7.8%		0.9%	10.0%	9.6%	2.6%	0.5%	
recovery	7.0%		0.7%	7.0%	10.6%	4.3%	0.4%	
expansion	8.9%		0.7%	13.1%	9.8%	2.8%	0.9%	
slowdown	7.1%		0.5%	11.1%	10.2%	2.7%	1.0%	

FSI

In-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		19%	0%	49%	32%	0%	
Recovery	0%		24%	0%	10%	66%	0%	
Expansion	0%		0%	51%	49%	0%	0%	
Slowdown	63%		0%	28%	0%	9%	0%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Avg Return	Quarterly returns (by 2018)							
contraction	0.0%		1.0%	-1.5%	2.2%	1.5%	0.3%	
recovery	-2.2%		0.9%	-0.6%	0.6%	1.6%	0.4%	
expansion	1.0%		1.0%	3.7%	3.6%	0.6%	0.3%	
slowdown	2.7%		1.1%	1.8%	-0.6%	1.3%	0.5%	
StDev	Quarterly returns (by 2018)							
contraction	7.4%		1.0%	7.9%	9.8%	2.6%	0.3%	
recovery	7.0%		0.9%	8.6%	9.9%	2.3%	0.6%	
expansion	9.2%		0.7%	9.7%	8.5%	3.3%	0.9%	
slowdown	6.9%		0.5%	14.3%	11.3%	3.3%	0.7%	

Out-of-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	14%		0%	33%	53%	0%	0%	
Recovery	0%		11%	89%	1%	0%	0%	
Expansion	18%		33%	0%	0%	48%	0%	
Slowdown	0%		7%	0%	33%	60%	0%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	9%		15%	25%	34%	17%	0%	
Recovery	0%		29%	37%	25%	8%	0%	
Expansion	6%		26%	12%	23%	32%	1%	
Slowdown	0%		12%	18%	18%	50%	2%	
Avg Return	Quarterly returns (by 2018)							
contraction	1.8%		0.9%	2.9%	4.1%	0.8%	0.3%	
recovery	0.1%		1.1%	3.1%	0.8%	0.8%	0.5%	
expansion	0.6%		0.9%	-1.9%	-0.6%	1.2%	0.3%	
slowdown	0.1%		1.0%	0.5%	2.0%	3.1%	0.7%	
StDev	Quarterly returns (by 2018)							
contraction	9.6%		0.8%	10.2%	7.7%	2.2%	0.5%	
recovery	7.6%		0.8%	7.8%	10.9%	3.9%	0.6%	
expansion	6.7%		0.6%	14.6%	10.2%	2.8%	0.9%	
slowdown	6.4%		0.8%	6.3%	12.1%	2.9%	0.7%	

	In-sample								
G/I	Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
	ng_ni	78%		0%	15%	0%	7%	0%	
	ng_i	0%		0%	42%	27%	31%	0%	
	g_ni								
	g_i	0%		16%	23%	61%	0%	0%	
	Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
	Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Avg Return								
	ng_ni	1.9%		0.6%	1.0%	0.8%	0.9%	0.5%	
	ng_i	0.4%		0.3%	1.4%	1.1%	1.2%	0.2%	
	g_ni								
	g_i	0.0%		1.7%	1.9%	2.6%	1.4%	0.4%	
	StDev	Quarterly returns (by 2018)							
	ng_ni	6.9%		0.4%	13.4%	10.0%	2.1%	0.8%	
	ng_i	6.3%		0.5%	10.1%	9.3%	2.3%	0.3%	
	g_ni								
	g_i	10.1%		0.6%	7.4%	9.8%	3.9%	0.6%	

Out-of-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
ng_ni	0%		0%	32%	66%	2%	0%	
ng_i	100%		0%	0%	0%	0%	0%	
g_ni	0%		0%	100%	0%	0%	0%	
g_i	60%		1%	0%	22%	17%	0%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
ng_ni	9%		4%	29%	52%	7%	0%	
ng_i	40%		12%	2%	23%	22%	0%	
g_ni	1%		10%	83%	0%	3%	0%	
g_i	60%		5%	5%	13%	18%	0%	
Avg Return	Quarterly returns (by 2018)							
ng_ni	-0.3%		1.1%	2.1%	3.1%	1.2%	0.4%	
ng_i	3.7%		0.8%	1.1%	-1.1%	1.5%	0.3%	
g_ni	1.1%		1.4%	4.0%	0.5%	1.2%	0.4%	
g_i	2.0%		0.4%	-4.1%	1.0%	0.8%	0.3%	
StDev	Quarterly returns (by 2018)							
ng_ni	8.6%		0.7%	9.4%	9.1%	2.7%	0.9%	
ng_i	6.1%		0.7%	8.7%	9.0%	3.2%	0.5%	
g_ni	8.2%		0.6%	8.6%	11.5%	4.2%	0.4%	
g_i	9.0%		0.8%	16.6%	9.7%	1.4%	0.6%	

Source: Authors

Table A. 9 Performance metrics for out-of-sample asset allocation for Japan

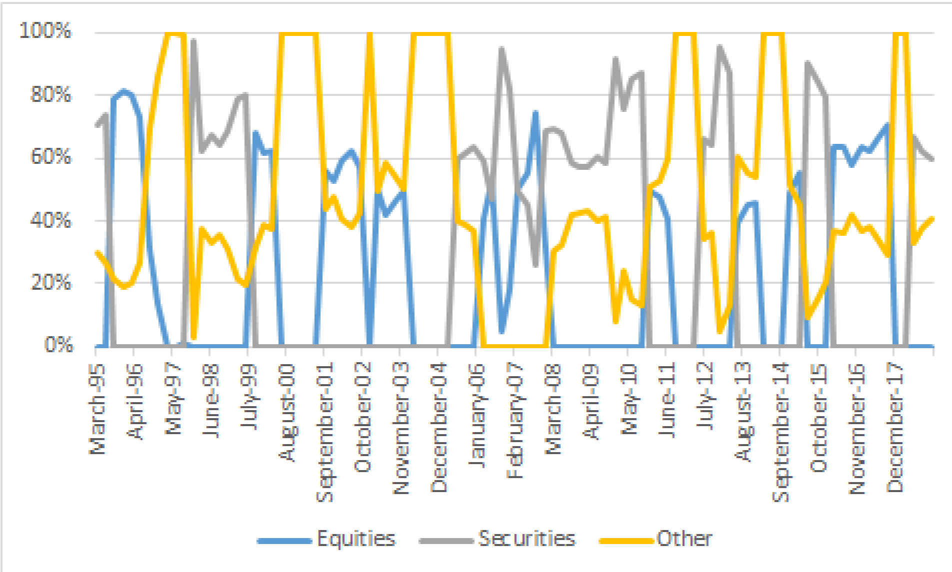
OOS	Balanced PF	FSI	CI	GDPI	ECI	GI	60/40	Equity only	Rf
1995-2018	Avg	0.08	0.06	0.08	0.10	0.08	0.05	0.09	0.04
1995-2018	StDev	0.20	0.26	0.24	0.32	0.29	0.23	0.42	0.10
1995-2018	Sharpe	0.17	0.07	0.15	0.19	0.12	0.04	0.13	0.00
2000-2018	Avg	0.06	0.06	0.06	0.11	0.07	0.04	0.09	0.03
2000-2018	StDev	0.19	0.26	0.22	0.32	0.28	0.23	0.40	0.08
2000-2018	Sharpe	0.14	0.13	0.16	0.25	0.16	0.06	0.14	0.00
2009-2018	Avg	0.04	0.06	0.02	0.08	0.08	0.08	0.15	0.03
2009-2018	StDev	0.16	0.27	0.21	0.27	0.22	0.22	0.39	0.05
2009-2018	Sharpe	0.11	0.12	-0.01	0.18	0.27	0.25	0.31	0.00
OOS	**Mod conc PF**	FSI	CI	GDPI	ECI	GI	60/40	Equity only	Rf
1995-2018	Avg	0.09	0.08	0.08	0.13	0.10	0.05	0.09	0.04
1995-2018	StDev	0.22	0.32	0.26	0.37	0.34	0.23	0.42	0.10
1995-2018	Sharpe	0.23	0.11	0.16	0.23	0.18	0.04	0.13	0.00
2000-2018	Avg	0.07	0.08	0.07	0.14	0.09	0.04	0.09	0.03
2000-2018	StDev	0.21	0.33	0.25	0.38	0.33	0.23	0.40	0.08
2000-2018	Sharpe	0.18	0.15	0.17	0.29	0.20	0.06	0.14	0.00
2009-2018	Avg	0.05	0.07	0.02	0.09	0.11	0.08	0.15	0.03
2009-2018	StDev	0.18	0.31	0.24	0.32	0.26	0.22	0.39	0.05
2009-2018	Sharpe	0.16	0.14	-0.04	0.21	0.32	0.25	0.31	0.00
OOS	**Concentrated PF**	FSI	CI	GDPI	ECI	GI	60/40	Equity only	Rf
1995-2018	Avg	0.10	0.11	0.10	0.13	0.12	0.05	0.09	0.04
1995-2018	StDev	0.28	0.40	0.36	0.42	0.39	0.23	0.42	0.10
1995-2018	Sharpe	0.20	0.16	0.15	0.22	0.21	0.04	0.13	0.00
2000-2018	Avg	0.07	0.12	0.10	0.16	0.11	0.04	0.09	0.03
2000-2018	StDev	0.27	0.42	0.37	0.44	0.38	0.23	0.40	0.08
2000-2018	Sharpe	0.14	0.22	0.19	0.30	0.22	0.06	0.14	0.00
2009-2018	Avg	0.08	0.13	-0.01	0.11	0.17	0.08	0.15	0.03
2009-2018	StDev	0.27	0.42	0.31	0.37	0.35	0.22	0.39	0.05
2009-2018	Sharpe	0.21	0.26	-0.12	0.24	0.40	0.25	0.31	0.00

Note: The table shows metrics for annualised quarterly total returns[62]; "Rf": Risk-free rate of total returns (100% investment in sovereign bonds); for a definition of the risk allocation strategies (i.e. the meaning of the cut-off values see section V.B).

Source: Authors

[62] i.e. a quarterly total return of 2.5% would enter the computation as 10.3%.

Figure A. 6: JP: Out-of-sample asset allocation for FSI over time



Note: Securities include government bonds. Figures are for moderately concentrated portfolio.

Source: Authors

Table A. 10 Asset allocation conditional on the stage of the cycle for the United Kingdom (balanced portfolio)

GDPI

In-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		0%	26%	0%	33%	41%	
Recovery	0%		0%	30%	57%	0%	13%	
Expansion	0%		0%	0%	47%	44%	9%	
Slowdown	0%		6%	0%	42%	52%	0%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		5%	30%	23%	31%	11%	
Recovery	0%		0%	22%	58%	8%	12%	
Expansion	0%		0%	5%	56%	26%	13%	
Slowdown	0%		2%	2%	56%	31%	9%	
Avg Return	Quarterly returns (by 2018)							
contraction	1.1%		1.6%	2.1%	1.7%	2.2%	2.3%	
recovery	0.5%		1.3%	3.4%	4.9%	1.7%	2.4%	
expansion	1.8%		1.4%	0.7%	2.9%	2.8%	2.0%	
slowdown	-1.5%		1.7%	-2.7%	2.6%	2.8%	1.6%	
StDev	Quarterly returns (by 2018)							
contraction	9.1%		1.0%	10.4%	8.5%	4.6%	4.3%	
recovery	6.8%		0.9%	8.3%	4.9%	3.3%	3.5%	
expansion	7.5%		1.1%	10.3%	7.3%	3.9%	2.8%	
slowdown	5.6%		1.2%	15.3%	9.4%	5.4%	3.0%	

Out-of-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		0%	0%	0%	32%	68%	
Recovery	0%		0%	29%	71%	0%	0%	
Expansion	0%		0%	0%	52%	48%	0%	
Slowdown	0%		0%	0%	44%	56%	0%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		1%	30%	29%	33%	8%	
Recovery	0%		0%	21%	75%	1%	3%	
Expansion	0%		0%	3%	75%	22%	0%	
Slowdown	0%		0%	2%	64%	34%	0%	
Avg Return	Quarterly returns (by 2018)							
contraction	1.1%		1.6%	2.1%	1.7%	2.2%	2.3%	
recovery	0.5%		1.3%	3.4%	4.9%	1.7%	2.4%	
expansion	1.8%		1.4%	0.7%	2.9%	2.8%	2.0%	
slowdown	-1.5%		1.7%	-2.7%	2.6%	2.8%	1.6%	
StDev	Quarterly returns (by 2018)							
contraction	9.2%		1.0%	10.4%	8.5%	4.6%	4.4%	
recovery	6.8%		0.9%	8.3%	4.9%	3.3%	3.5%	
expansion	7.5%		1.1%	10.3%	7.3%	3.9%	2.8%	
slowdown	5.6%		1.2%	15.3%	9.4%	5.4%	3.0%	

ECI

In-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		0%	0%	18%	49%	33%	
Recovery	0%		0%	0%	71%	23%	6%	
Expansion	21%		0%	58%	21%	0%	0%	
Slowdown	0%		0%	0%	66%	19%	16%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		1%	24%	34%	28%	13%	
Recovery	0%		0%	10%	38%	41%	11%	
Expansion	3%		0%	22%	60%	8%	7%	
Slowdown	0%		0%	38%	46%	9%	7%	
Avg Return	Quarterly returns (by 2018)							
contraction	1.6%		1.5%	-1.1%	1.9%	2.5%	2.2%	
recovery	-1.2%		1.7%	2.0%	3.4%	2.4%	2.1%	
expansion	2.7%		1.4%	3.4%	2.7%	2.2%	2.2%	
slowdown	-0.7%		1.2%	1.7%	3.3%	2.1%	2.0%	
StDev	Quarterly returns (by 2018)							
contraction	7.3%		1.0%	14.8%	8.6%	4.3%	4.2%	
recovery	9.1%		1.2%	8.8%	7.5%	5.2%	3.9%	
expansion	8.7%		1.0%	8.1%	7.7%	4.2%	3.6%	
slowdown	4.5%		1.0%	8.5%	7.2%	2.6%	2.4%	

Out-of-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		0%	0%	0%	67%	33%	
Recovery	0%		0%	0%	80%	20%	0%	
Expansion	0%		0%	100%	0%	0%	0%	
Slowdown	0%		0%	0%	94%	6%	0%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		1%	26%	31%	34%	7%	
Recovery	0%		0%	7%	33%	57%	3%	
Expansion	6%		0%	27%	67%	0%	0%	
Slowdown	0%		0%	29%	49%	15%	7%	
Avg Return	Quarterly returns (by 2018)							
contraction	1.6%		1.5%	-1.1%	1.9%	2.5%	2.2%	
recovery	-1.2%		1.7%	2.0%	3.4%	2.4%	2.1%	
expansion	2.7%		1.4%	3.4%	2.7%	2.2%	2.2%	
slowdown	-0.7%		1.2%	1.7%	3.3%	2.1%	2.0%	
StDev	Quarterly returns (by 2018)							
contraction	7.3%		1.0%	14.8%	8.6%	4.3%	4.2%	
recovery	9.1%		1.2%	8.8%	7.5%	5.2%	3.9%	
expansion	8.7%		1.0%	8.1%	7.7%	4.2%	3.6%	
slowdown	4.5%		1.0%	8.5%	7.2%	2.6%	2.4%	

	In-sample								
CI	Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
	Contraction	0%		0%	0%	16%	61%	23%	
	Recovery	0%		0%	0%	67%	30%	3%	
	Expansion	0%		0%	0%	52%	19%	29%	
	Slowdown	0%		0%	51%	0%	21%	28%	
	Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
	Contraction	0%		14%	29%	24%	29%	3%	
	Recovery	0%		12%	8%	60%	20%	0%	
	Expansion	0%		0%	0%	55%	28%	17%	
	Slowdown	0%		6%	22%	15%	38%	19%	
	Avg Return	Quarterly returns (by 2018)							
	contraction	0.5%		1.5%	1.0%	1.6%	2.1%	1.7%	
	recovery	1.7%		1.6%	1.7%	4.4%	2.9%	1.8%	
	expansion	1.3%		1.5%	1.3%	4.9%	2.8%	3.4%	
	slowdown	-0.8%		1.1%	2.1%	-1.4%	1.5%	1.7%	
	StDev	Quarterly returns (by 2018)							
	contraction	7.8%		1.2%	12.9%	7.8%	5.0%	3.8%	
	recovery	6.8%		0.8%	6.9%	5.4%	3.8%	2.8%	
	expansion	8.8%		1.0%	11.3%	8.7%	3.7%	4.4%	
	slowdown	9.2%		0.9%	7.2%	7.9%	3.7%	2.4%	

Out-of-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		0%	0%	0%	86%	14%	
Recovery	0%		0%	0%	71%	29%	0%	
Expansion	0%		0%	0%	78%	0%	22%	
Slowdown	0%		0%	80%	0%	0%	20%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		13%	30%	25%	32%	1%	
Recovery	0%		10%	2%	79%	9%	0%	
Expansion	0%		0%	0%	71%	23%	6%	
Slowdown	0%		0%	21%	23%	43%	14%	
Avg Return	Quarterly returns (by 2018)							
contraction	0.5%		1.5%	1.0%	1.6%	2.1%	1.7%	
recovery	1.7%		1.6%	1.7%	4.4%	2.9%	1.8%	
expansion	1.3%		1.5%	1.3%	4.9%	2.8%	3.4%	
slowdown	-0.8%		1.1%	2.1%	-1.4%	1.5%	1.7%	
StDev	Quarterly returns (by 2018)							
contraction	7.8%		1.2%	12.9%	7.8%	5.0%	3.8%	
recovery	6.8%		0.8%	6.9%	5.4%	3.8%	2.8%	
expansion	8.8%		1.0%	11.3%	8.7%	3.7%	4.4%	
slowdown	9.2%		0.9%	7.2%	7.9%	3.7%	2.4%	

	In-sample								
FSI	Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
	Contraction	0%		0%	85%	12%	3%	0%	
	Recovery	0%		0%	0%	36%	49%	15%	
	Expansion	0%		0%	0%	37%	30%	32%	
	Slowdown	19%		0%	46%	35%	0%	0%	
	Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
	Contraction	0%		1%	74%	12%	12%	2%	
	Recovery	0%		0%	8%	31%	53%	9%	
	Expansion	0%		0%	0%	47%	26%	27%	
	Slowdown	15%		1%	53%	28%	3%	1%	
	Avg Return	Quarterly returns (by 2018)							
	contraction	0.6%		1.7%	5.9%	2.8%	2.4%	2.3%	
	recovery	0.5%		1.2%	-0.7%	2.4%	2.8%	1.7%	
	expansion	0.6%		1.6%	-1.3%	2.8%	2.5%	2.6%	
	slowdown	2.6%		1.2%	4.1%	3.5%	0.1%	1.6%	
	StDev	Quarterly returns (by 2018)							
	contraction	8.6%		1.1%	10.5%	9.4%	5.2%	4.6%	
	recovery	6.0%		1.0%	11.8%	7.0%	3.5%	2.9%	
	expansion	8.4%		1.0%	9.7%	8.2%	4.3%	3.6%	
	slowdown	9.7%		0.8%	9.6%	2.7%	3.3%	3.0%	

Out-of-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%	0%	0%	91%	9%	0%	0%	0%
Recovery	0%	0%	0%	0%	38%	62%	0%	0%
Expansion	0%	0%	0%	0%	76%	0%	24%	0%
Slowdown	0%	0%	0%	63%	37%	0%	0%	0%
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
Contraction	0%		0%	87%	1%	10%	3%	
Recovery	0%		0%	0%	50%	50%	0%	
Expansion	0%		0%	0%	69%	16%	16%	
Slowdown	9%		0%	62%	29%	0%	0%	
Avg Return	Quarterly returns (by 2018)							
contraction	0.6%		1.7%	5.9%	2.8%	2.4%	2.3%	
recovery	0.5%		1.2%	-0.7%	2.4%	2.8%	1.7%	
expansion	0.6%		1.6%	-1.3%	2.8%	2.5%	2.6%	
slowdown	2.6%		1.2%	4.1%	3.5%	0.1%	1.6%	
StDev	Quarterly returns (by 2018)							
contraction	8.6%		1.1%	10.5%	9.4%	5.2%	4.6%	
recovery	6.0%		1.0%	11.8%	7.0%	3.5%	2.9%	
expansion	8.4%		1.0%	9.7%	8.2%	4.3%	3.6%	
slowdown	9.7%		0.8%	9.6%	2.7%	3.3%	3.0%	

G/I	In-sample								
	Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
	ng_ni	0%		0%	0%	39%	21%	40%	
	ng_i	0%		0%	0%	50%	30%	20%	
	g_ni	77%		0%	2%	0%	21%	0%	
	g_i	0%		0%	57%	42%	1%	0%	
	Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
	Contraction	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Recovery	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Expansion	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Slowdown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Avg Return								
	ng_ni	1.0%		0.2%	-0.9%	1.8%	1.4%	1.8%	
	ng_i	-1.0%		2.2%	0.9%	4.6%	3.6%	3.1%	
	g_ni	2.4%		1.3%	1.5%	1.3%	1.8%	1.5%	
	g_i	0.9%		2.9%	4.8%	4.3%	2.9%	2.1%	
	StDev	Quarterly returns (by 2018)							
	ng_ni	8.1%		0.0%	10.4%	6.2%	3.5%	2.9%	
	ng_i	9.3%		0.7%	6.6%	7.0%	5.4%	4.4%	
	g_ni	6.0%		0.3%	14.7%	8.5%	3.2%	3.9%	
	g_i	10.1%		0.7%	7.7%	9.1%	4.9%	3.5%	

Out-of-sample								
Asset allocation (by end 2018)	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
ng_ni	0%		0%	0%	73%	18%	9%	
ng_i	0%		0%	0%	23%	40%	37%	
g_ni	0%		0%	89%	7%	4%	0%	
g_i	25%		30%	0%	0%	43%	0%	
Average allocation over time	Gold	Real E	Cash	Commodities	Equities	Sov Bonds	Corp IG	Corp HY
ng_ni	18%		0%	5%	60%	10%	6%	
ng_i	4%		3%	0%	16%	51%	27%	
g_ni	0%		3%	50%	14%	23%	12%	
g_i	0%		23%	49%	22%	13%	1%	
Avg Return	Quarterly returns (by 2018)							
ng_ni	0.4%		1.8%	0.3%	5.1%	2.6%	2.2%	
ng_i	1.3%		1.1%	-1.0%	2.3%	3.0%	2.8%	
g_ni	1.0%		1.7%	3.9%	2.0%	1.9%	1.8%	
g_i	1.1%		1.3%	-0.7%	-0.1%	1.9%	-0.2%	
StDev	Quarterly returns (by 2018)							
ng_ni	5.5%		0.5%	7.0%	6.2%	3.9%	3.4%	
ng_i	12.2%		1.3%	14.2%	8.1%	5.2%	5.5%	
g_ni	6.8%		1.1%	10.0%	8.4%	4.0%	2.4%	
g_i	9.2%		1.8%	11.8%	7.9%	4.1%	4.7%	

Source: Authors

Table A. 11 Performance metrics for out-of-sample asset allocation for the UK

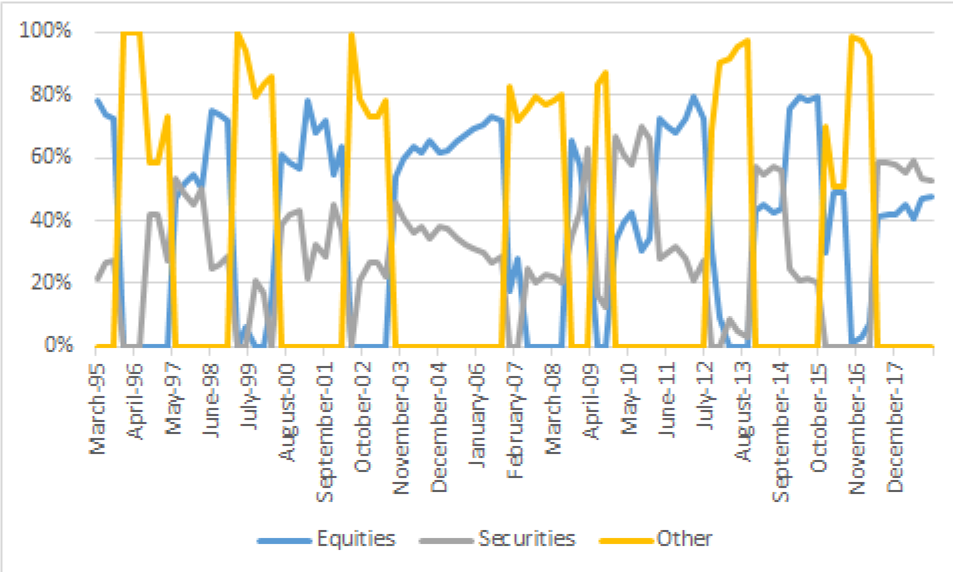
OOS	Balanced PF	FSI	CI	GDPI	ECI	GI	60/40	Equity only	Rf
1995-2018	Avg	0.12	0.07	0.08	0.07	0.12	0.08	0.11	0.08
1995-2018	StDev	0.27	0.22	0.23	0.20	0.29	0.18	0.30	0.14
1995-2018	Sharpe	0.15	-0.05	0.01	-0.04	0.15	0.02	0.11	0.00
2000-2018	Avg	0.10	0.04	0.07	0.05	0.11	0.06	0.08	0.07
2000-2018	StDev	0.28	0.22	0.25	0.18	0.30	0.16	0.29	0.14
2000-2018	Sharpe	0.11	-0.14	0.00	-0.11	0.15	-0.07	0.03	0.00
2009-2018	Avg	0.07	0.05	0.07	0.06	0.06	0.08	0.12	0.06
2009-2018	StDev	0.29	0.21	0.30	0.20	0.22	0.17	0.30	0.14
2009-2018	Sharpe	0.03	-0.03	0.01	-0.01	-0.01	0.13	0.21	0.00
OOS	**Mod conc PF**	FSI	CI	GDPI	ECI	GI	60/40	Equity only	Rf
1995-2018	Avg	0.14	0.08	0.10	0.07	0.14	0.08	0.11	0.08
1995-2018	StDev	0.33	0.26	0.33	0.22	0.33	0.18	0.30	0.14
1995-2018	Sharpe	0.18	0.00	0.07	-0.03	0.18	0.02	0.11	0.00
2000-2018	Avg	0.11	0.04	0.10	0.05	0.13	0.06	0.08	0.07
2000-2018	StDev	0.34	0.24	0.36	0.20	0.33	0.16	0.29	0.14
2000-2018	Sharpe	0.13	-0.10	0.08	-0.08	0.18	-0.07	0.03	0.00
2009-2018	Avg	0.07	0.06	0.09	0.07	0.06	0.08	0.12	0.06
2009-2018	StDev	0.35	0.24	0.44	0.23	0.23	0.17	0.30	0.14
2009-2018	Sharpe	0.03	0.01	0.07	0.05	-0.02	0.13	0.21	0.00
OOS	**Concentr ated PF**	FSI	CI	GDPI	ECI	GI	60/40	Equity only	Rf
1995-2018	Avg	0.17	0.10	0.13	0.08	0.16	0.08	0.11	0.08
1995-2018	StDev	0.45	0.30	0.37	0.28	0.38	0.18	0.30	0.14
1995-2018	Sharpe	0.21	0.07	0.14	0.01	0.21	0.02	0.11	0.00
2000-2018	Avg	0.14	0.07	0.12	0.05	0.15	0.06	0.08	0.07
2000-2018	StDev	0.46	0.29	0.39	0.26	0.38	0.16	0.29	0.14
2000-2018	Sharpe	0.16	0.00	0.13	-0.05	0.21	-0.07	0.03	0.00
2009-2018	Avg	0.09	0.09	0.09	0.12	0.05	0.08	0.12	0.06
2009-2018	StDev	0.46	0.26	0.46	0.27	0.26	0.17	0.30	0.14
2009-2018	Sharpe	0.07	0.10	0.06	0.20	-0.04	0.13	0.21	0.00

Note: The table shows metrics for annualised quarterly total returns[63]; "Rf": Risk-free rate of total returns (100% investment in sovereign bonds); for a definition of the risk allocation strategies (i.e. the meaning of the cut-off values see section V.B).

Source: Authors

[63] i.e. a quarterly total return of 2.5% would enter the computation as 10.3%.

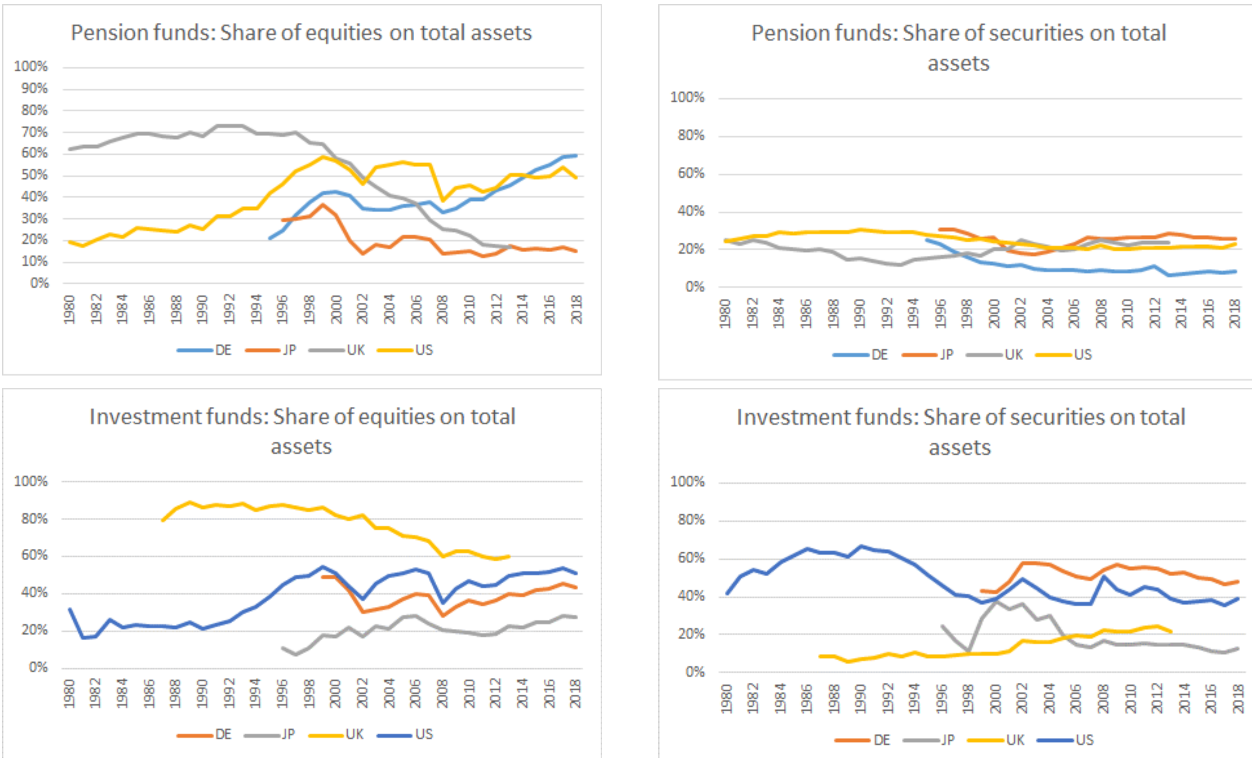
Figure A. 7: GB: Out-of-sample asset allocation for FSI over time



Note: Securities include government bonds. Figures are for moderately concentrated portfolio.

Source: Authors

Figure A. 8: Asset composition of institutional investors



Source: Authors, based on data from [OECD Institutional Investor Statistics]

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An empirical analysis

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