Milliman Research Report

Prepared by:

Innova Asset Management Dan Miles, BComm, BSc, PGCertAppFin

Milliman Stuart Reynolds, FIA Fred Vosvenieks, FIA, CERA

JANUARY 2015





TABLE OF CONTENTS

9	REFERENCES	48
8	ACKNOWLEDGEMENTS	48
7	APPENDIX B: EX-POST ANALYSIS	44
	6.2 Bayesian network model for bond returns6.3 Combined Bayesian model	38 42
0	6.1 Bayesian network model for equity returns	29 29
6	APPENDIX A' CALIBRATING A BAYESIAN NETWORK MODEL	20
5	CONCLUSION	28
	4.4 ALM for financial advice	26
	4.3 Portfolio construction	24 26
	4.1 Othern hisk appende 4.2 Stress and scenario testing	∠∠ 24
4	USE GASES	22
	3.3 An example Dayesian network risk factor model	19
	3.2 Use of Bayesian networks in risk factor modelling	19
	3.1 Bayesian networks background	19
3	RISK FACTOR MODELLING	19
	2.7 Summary	18
	2.6 Practical challenges of risk factor asset allocation	18
	2.5 Risk factor portfolio performance versus traditional approaches	17
	2.4 What does a risk factor portfolio look like?	15
	2.3 Stability of correlations	14
	2.2 Benefits of risk factor asset allocation	11
2	2.1 Traditional portfolio construction	8
2	PORTFOLIO CONSTRUCTION AND MANAGEMENT	8
	1.3 Capturing risk factors	5
	1.1 VVIal are lisk lactors: 1.2 Risk factor examples	2
1	1 1 What are risk feeters?	2
4	DISKEACTORS	0

1 RISK FACTORS

1.1 What are risk factors?

The concept of a 'risk factor' stems from the belief that the returns on an asset can be broken down or split up into distinct sub-components that each contribute to the overall return and risk characteristics of the asset. Extending this into portfolio management, Podkaminer (2013) likened risk factors to atoms and assets to molecules. For example, the return earned on a corporate bond can be broken down according to the risks to which the bond holder is exposed, including duration, inflation and credit risks.

Over recent years, risk factor investment frameworks have started to reach into mainstream academic and practitioner literature. However, there remains no universally accepted definition that describes them; confusingly and unhelpfully, they are also variously referred to as 'risk premias', 'betas', 'smart betas' and even 'scientific betas'.

In this paper we define a risk factor as a causal driver of asset returns which has risk, return and relationship characteristics with other risk factors. All risk factors have a degree of uncertainty or risk associated with them, and a corresponding risk premium which may be positive or negative. Some authors have chosen to focus on a less granular measure, risk premia–an asset's return relative to a risk-free rate. However, studying risk factors permits a more refined distinction to be made between uncertainty and return and therefore provides much greater insight into the causes of the differences in return between assets.

1.2 Risk factor examples

FIGURE 1: COMPONENT RISK FACTORS THAT DRIVE FIXED-INCOME YIELDS

To illustrate what we mean by risk factors, in Figure 1 below we consider the yield components for various fixed-income assets. The green bars represent the total yield on each of five different types of fixed-income asset, with the blue boxes showing the component factors that contribute to the yield available.





One can see the different risk factor building blocks that make up the yield that is available on each of these assets.

There is no universal agreement on the appropriate taxonomy of risk factors that govern asset class returns. Figure 2 below outlines the approaches that various institutions have taken to defining and using various risk factors.

FIGURE 2: SUMMARY OF RISK FACTORS USED BY VARIOUS INSTITUTIONS										
ENTITY	FIXED INCOME	EQUITY	OTHER							
Norway Government Pension Fund (Nagy 2010)	Term, credit Aa, credit Baa, credit high-yield	Value / growth, small cap / large cap, momentum, volatility	FX carry, liquidity							
Danish Pension Fund PKA (Rohde et al 2010)	Interest rates, credit	Equity (developed / emerging / frontier markets, small cap, low volatility, dividends, implied volatility, momentum, value, quality, merger arbitrage, liquidity, other)	Commodities, inflation-protected assets (ILB, real estate, infrastructure)							
Blackrock (Ransenberg 2012)	Real rates, inflation, credit		Liquidity, political, economic							
Deutsche Bank (Jones 2011)	Duration, credit, illiquidity	Size, value, momentum	Commodity, alternatives, growth, inflation volatility, liquidity, carry							
Goldman Sachs (O'Neill 2013)	Real rates	Equity risk premium	Real assets (e.g. gold, real estate, commodities)							
Goldman Sachs (Asl et al 2012)	Term	Equity	Funding, liquidity, FX, emerging markets							
PIMCO (Parikh 2012)	Real rates, inflation, term	Multi-factor productivity, dividend yields, growth (earnings, GDP), valuation levels (PE, treasury yields)	Volatility							

Briand et al (2009) outline the risk premia framework that MSCI Barra¹ use for modelling asset returns. They define three categories of risk premia:

- 1. Asset-class Excess returns above cash arising from the bearing of risk relative to a cash investment.
- 2. Style Returns relating to certain common characteristics across securities.
- 3. Strategy Returns derived from a particular investment strategy.

The return on any portfolio can be decomposed into these 'beta' return elements, plus an 'alpha' return element accounting for non-systematic/relative fund returns. Indeed, they argue that much of what most fund managers call traditional 'alpha' is in fact 'beta' exposure to risk premia. Notably, Deutsche Bank (Jones 2011) uses a very similar categorisation into asset class, style and systemic/macro, with the latter relating to growth, inflation volatility and liquidity.

¹ MSCI is a provider of investment decision support tools including indices, portfolio risk and performance analytics and governance tools.

Regardless of the ultimate purpose, one of the first steps is to identify the various asset risk factors that may be of interest or to which an existing investment may be exposed. Instead of undertaking this at the security level, it is perhaps easiest to start with a qualitative mapping of risk factors to asset classes, as shown in the figures below.

FIGURE 3: RISK FACTORS FOR FIXED-INCOME ASSET CLASSES											
FIXED INCOME	REAL CASH	ACTUAL INFLATION	EXPECTED INFLATION	DURATION	CREDIT / DEFAULT	LIQUIDITY	GEO. / POLITICAL				
Official cash	~	~									
Bank bills	v	v	v								
Inflation swaps		v	v								
Inflation-indexed gov't bonds	v	v		v							
Nominal gov't bonds	v		v	V							
Inflation-indexed corporate bonds	V	V		V	~						
Nominal investment-grade corp. bonds	~		V	~	V						
High-yield bonds	v		v	V	v	v					
Emerging sovereign bonds	v		v	V	v	v	V				
Global investment-grade bonds hedged	~		V	~	V		V				
Global high-yield	v		v	V	~	V	v				
Infrastructure	v	~	v	V	~	v	v				

FIGURE 4: RISK FACTORS FOR EQUITIES

EQUITIES	DIVIDEND YIELDS	EARNING GROWTH	VALUATION (P/E)	SECTOR / INDUSTRY	STYLE FACTORS	GEO. / POLITICAL	CURRENCY
Dividend swaps	~						
Index futures		v	~				
Market index	~	v	v				
Large / small cap, growth / value, momentum	V	V	V		V		
Sector index	~	v	~	v			
Developed markets	v	v	v			V	V
Emerging markets	v	v	v			V	

FIGURE 5: RISK FACTORS FOR PROPERTY AND INFRASTRUCTURE											
OTHER	CASH FLOW YIELDS	INFLATION	EARNING GROWTH	VALUATION (P/NTA)	LIQUIDITY	GEO. / POLITICAL					
Property	~	V	~	~	~						
Infrastructure	v	~	~	~	~	~					

There are many more asset classes that could be added to the above lists. We agree with Bhansali et al (2012) in that whilst there is a vast array of asset classes, there are only a relatively small number of risk factors. This is perhaps not surprising, given that securities are fundamentally calls on the income generated by a private entity, a group of individuals or a government body, each of which is subject to similar economic, environmental, political and social drivers. Of these, Bhansali et al. find that within their framework, global growth and global inflation are the two dominant factors in determining asset class returns.

1.3 Capturing risk factors

As a general rule, there are currently few risk factors which can be captured directly. Some risk factors are easier to invest in than others with the creation of investable proxies, such as indices. However, some factors are currently very difficult, if not impossible, to gain investment exposure to directly, such as GDP growth. In essence, many risk factors can be captured by taking a combination of long and short positions or by using a derivative-based strategy.

There are numerous examples in practitioner and academic literature of strategies to capture factors. Figure 6 outlines some non-exhaustive examples of each of these risk factors used within the MSCI Barra framework, along with the investment strategy that can be used to gain exposure to each type of risk premia.

FIGURE 6: RISK PREMIA USED BY MSCI BARRA (SOURCE: BRIAND ET AL 2009)											
ASSET CLASS	ASSET CLASS BETA	STYLE BETA	STRATEGY BETA								
Fixed Income	Broad fixed-income markets	Credit spreads, high-yield spread, term structure spread	Convertible arbitrage								
Equity	Broad equity markets	Size, value, momentum	Merger arbitrage								
Currency	Broad currency markets		Carry trade, value, momentum								
	ASSET CLASS STRATEGY USED TO	GAIN EXPOSURE									
	Long short positions										

1.3.1 Real cash

Every asset class compensates investors for the time value of their money, as measured by the real cash rate. The most obvious ones are nominal cash (overnight and bank bills) and short-dated inflation indexed bonds, both of which compensate the investor for 'actual' inflation over the very near term.

Example investment strategies:

- Buy cash.
- Buy short-dated, inflation-indexed government bonds.

1.3.2 Inflation risk premium

1.3.2.1 Actual inflation

Inflation-linked bonds offer a readily accessible means of obtaining actual inflation returns, as their payoffs are a direct function of an inflation index. This type of investment can mitigate against the risk of inflation over long durations. Note that this does not consider potential basis risk between the inflation index and the investor's personal inflation rate. Over short durations, say out to 90 days, money market instruments such as bank bills will effectively provide returns linked to actual inflation. This is because market estimates of short-term inflation are generally very good, with relatively low residual risk.

An alternative way of accessing actual inflation is to use inflation derivatives, notably inflation swaps, which exchange payments based upon a fixed rate for ones based upon an inflation index. This is a zero-dollar investment that has a payoff of the excess of realised inflation over expected inflation. By investing capital in cash and entering into this derivative, the investor receives nominal cash (real cash plus actual short-term inflation), plus the excess of realised inflation over expected inflation. As such contracts are OTC, they involve an additional risk factor, the credit risk of the counterparty. Such credit risk can be largely or wholely mitigated through the use of collateralisation techniques or credit default swaps.

1.3.2.2 Expected inflation

Assets with cash flows that are denominated in nominal terms are effectively compensating investors for expected rather than actual inflation. This is because their market prices are set such that the nominal cash flows provide the investor sufficient compensation for their expectation of inflation, with no guarantee that this will be equal to actual inflation. Nominal bonds, particularly government bonds, provide expected inflation returns, although they also come bundled with duration returns. Corporate bonds also provide expected inflation returns, although they also come with additional credit risk (which can be mitigated), as well as duration risk.

As investors are subject to inflation risk by investing in nominal fixed-income securities, they typically demand an inflation risk premium to compensate them for this risk. The difference between nominal and real yields at equivalent durations will reflect this inflation risk premium in addition to the best estimate of future inflation. These two components together are known as the breakeven inflation rate, as they represent the rate at which inflation needs to be over the investment horizon in order for investment returns from nominal and inflation-indexed securities to be equal.

Perhaps the cleanest source of expected inflation is through inflation swaps, where the investor takes the side of paying inflationindexed cash flows and receiving fixed cash flows. This is a zero-dollar investment that has a payoff of the excess of expected inflation over realised inflation. By investing capital in cash and entering into this derivative, the investor receives nominal cash (real cash plus actual short-term inflation), plus the excess of expected inflation over realised inflation.

Example investment strategies:

- Buy nominal government bonds and sell (i.e. short) inflation-indexed government bonds.
- Long a nominal Treasury index and sell (i.e. short) a Treasury inflation-protected security index.²

1.3.3 Duration risk premium

Duration risk premium represents the additional risk premium that investors require in order to compensate them for being subject to capital risk. The duration risk premia is typically measured as the difference between the yield on a government bond and that of cash. It can be difficult to disentangle this risk premium from that of the inflation risk premium, as inflation expectations are not directly observable in the market (they are subjective estimates typically sourced from surveys).

The purest way to invest in the duration risk premium is to borrow continuously at the cash rate and invest in long-dated bonds. The difference in the bond cash inflows and the accumulated debt will be the duration risk premium (which can be negative). Clearly, the size of the duration risk premium in this instance will be dictated by the rate at which the institution or individual can borrow at, which may be higher than the yield on the bond, giving rise to a negative duration risk premium. Due to this reason, most institutions and individual investors access the duration premium through long-only investments directly in government bonds.

Example investment strategies:

- Buy nominal government bonds and borrow cash.
- Long a Treasury 20+ years index and sell (short) a Treasury 1- to 3-year index.³

1.3.4 Credit risk premium

The yield on a corporate bond relative to a government of equivalent duration, currency, etc. will contain a level of compensation for the expected level of default on the corporate bond. However, investors in such bonds will also require compensation for being exposed to this risk of default. In theory, all bonds come with some risk of default, though bonds issued by governments, especially those of developed countries, are traditionally considered to be free of default risk and hence the associated yield does not contain a credit risk premium. Bonds issued by corporate entities will carry a credit risk premium linked to the perceived creditworthiness of the bond. This will typically be measured by its credit rating.

To capture the credit risk premium, one could hold some combination of government and corporate debt. Sometimes capturing the credit risk premium in this way also captures other risk premia associated with corporate debt, such as the liquidity premium due to the lower marketability compared with government debt.

An alternative method to capture credit risk premium (for a specific company) would be to invest in derivative instruments such as credit default swaps (CDSs). Under a CDS, the investor pays a premium(s) and in return receives a payment if the issuing company defaults on its bond payments. CDSs are usually OTC derivatives and therefore come packaged with a premium to cover the associated risk of the CDS writer defaulting on the contract.

Example investment strategies:

- Long in US high-quality credit index and sell (short) US Treasury index.⁴
- Enter into a credit default swap.
- Buy a company's nominal corporate debt and sell (short) nominal government bonds (of the same duration).

² See Podkaminer, 2013

³ See Podkaminer, 2013

⁴ See Podkaminer, 2013

1.3.5 Volatility risk premium

The return from securities with a volatile value will contain a volatility risk premium to compensate investors for bearing the risk of actual volatility differing from expected volatility. This may occur in times of market turmoil and high investor uncertainty. A volatility risk premium is normally associated with investments such as equities and derivative instruments, but could theoretically apply to any security.

Example investment strategies:

- Buy an option (call or put) and delta hedge it.
- Enter into a variance swap (pay fixed receive realised volatility).

1.3.6 Liquidity risk premium

The return on investments that are illiquid will tend to contain a liquidity risk premium. Typical examples of such investments include infrastructure, direct property and venture capital. However, liquidity risk premiums can also be found in more standardised and liquid asset classes, such as:

- Treasury bonds, where off-the-run⁵ bonds tend to trade at lower prices relative to on-the-run bonds.
- Corporate bonds, which typically have liquidity during normal market conditions, but for which demand can evaporate under stressed capital market conditions.

Example investment strategies:

- Buy off-the-run and sell on-the-run treasury bonds.
- Invest directly into illiquid asset classes such as infrastructure, direct property and venture capital.

1.3.7 Geographic risk premium

The same securities in different countries can trade at significant premiums to one another, reflecting the different drivers of risk factors in each country. A good example of this is in the European Union (EU), whereby government bonds will trade at very different levels for countries within the EU, reflecting the different likelihoods of default, despite a high degree of economic and financial interdependence amongst them.

Example investment strategies:

 Buy foreign government bonds and hedge the currency risk. This results in an investor return of the domestic cash rate plus the foreign government duration risk premium.

1.3.8 Value premium

This is a 'Fama and French' type of risk factor relating to investment in equities. The premium arises due to the difference in return achieved (and risk taken on) by investing in value stocks (stocks thought to be undervalued) and growth stocks (stocks that are expected to increase in value at a rate over and above the market average).

Example investment strategies:

- Long a developed country equity value index and short a developed country equity growth index.⁶
- Long MSCI Value index and sell (short) MSCI Growth index.⁷

1.3.9 Size premium

This is another 'Fama and French' type of risk factor relating to investment in equities. Such a premium arises due to the additional risk associated with equity investment in small-sized companies, often measured by their market capitalisation.

Example investment strategies:

- Long a developed country equity small-cap index and short a developed country large-cap index.⁸
- Long Russell 3000 Index and sell (short) Russell 1000 Index.⁹

5 On-the-run bonds are those that represent the 1-, 3- and 10-year maturities, which are in higher demand compared with bonds at other maturities, referred to as off-the-run bonds.

- 6 See Podkaminer. 2013
- 7 See Briand et al.
- 8 See Podkaminer, 2013
- 9 See Izodrek, (2013)

2 PORTFOLIO CONSTRUCTION AND MANAGEMENT

2.1 Traditional portfolio construction

Investment portfolio construction has traditionally centred on the idea that by investing across uncorrelated assets, usually termed 'asset classes', a superior outcome in terms of risk versus return can be achieved. In work carried out by Harry Markowitz in the 1950s, such an optimal portfolio was thought to contain about 60% US equities and 40% US government bonds. Since then, this approach has been widely adopted and has led to investment strategies that combined:

- 'Growth' assets, which will provide you with a positive return premium above cash (US equities in the example above).
- 'Defensive' assets, which will perform well and smooth out overall returns in times of stress (US government bonds).

However, all too often, the concept of risk has been equated with a single measure, volatility, which is at best a proxy for the uncertainty associated with future asset returns. Alongside the simplifying assumption of fixed correlations between asset classes, strategies that were intended to provide both growth and protection too often provided neither to the end investor. This is demonstrated by the figure below: a 110-year chart of the drawdowns (the peak-to-trough decline during a specific period) that a 60/40 Australian equity/bond portfolio experienced.





Source: Milliman based upon Global Financial Data

Essentially, if 'growth assets' go down, the whole portfolio goes down. In other words, the concept of risk reduction has been completely misunderstood.

In an attempt to reduce the level of risk within investment portfolios, advisers and money managers have tried to increase diversification to reduce risk by investing in 'new' asset classes, instead of just equities and bonds. This has included property, infrastructure, distressed debt, commodities and various hedge fund strategies. However, even with increased investment in a wider range of assets, diversification is no guarantee of increased risk protection, particularly during times of stress when it is needed most. Under the asset class method of constructing investment portfolios, ideally the asset classes should be independent of one another and cover the whole investible universe. If we look through the lens of a risk factor framework, most of these 'asset classes' are exposed to the same risks as either equities or bonds–or both. Furthermore, some of these exposures will only become obvious in times of stress, when the lack of independence can be particularly detrimental to the performance of the portfolio.

In the figure below, we have reproduced a portfolio that looks like it is well diversified and is a broad representation of a typical 'balanced' portfolio, including various 'diversifying' asset classes. This portfolio's asset allocation is compared with its risk allocation in both the short (1 year) and long term (10 years). Risk allocation is derived based upon the impact of downside stress tests, which vary from short to long term.



Source: Milliman Australia and Innova Asset Management

Please note that in this example we have assumed a starting valuation of all assets to be aligned with long-term averages; therefore, over the long term, change in price due to change in market valuation should theoretically be negligible.¹⁰ As can be seen from the above, the underlying risk factor exposure depends on over which time horizon the portfolio is viewed. In the short term, inflation and valuation are the main drivers of risk whereas over the long term, risk is driven by inflation and economic growth. Over both time horizons, whilst the number of asset classes used in the above portfolio is large, the diversification of risk is not.

We can observe that the historical weaknesses in constructing resilient portfolios have been driven by a fundamental misunderstanding of the dynamics of risk and the sources of uncertainty. A focus on the allocation of capital rather than risk means that traditional approaches fail to capture the common causal drivers that exist across issuers, geographical locations and asset classes, and how they change over time.

¹⁰ However, in any particular year, asset classes-particularly equities-will trade above or below long-term average market valuation; therefore, valuation risk is likely to be a much larger component of long-term risk allocation. Refer to section 2.2 for further detail.

Some of the main problems with the traditional approach are that:

- The 60/40 result was very specific for the particular time period and data set for which it was tested.
- Volatility/standard deviation is used as the primary measure of risk.
- Traditional portfolios have almost all of their risk budget tied up in equities.
- This large exposure to equities leads to over-exposure to the drivers of equity risk.
- These same equity risk drivers may also exist in other asset classes (including 'new' ones), meaning that portfolios are not as diversified as they seem.

In addition to the above problems, much of the academic and mathematical background to the optimisation techniques used in traditional portfolio construction require a vast amount of data to calibrate for items such as the expected return of each asset, the standard deviations and the correlations between assets. The results are also very sensitive to the initial assumptions which place a great reliance on the quality of the data and associated statistical analyses. Perhaps most importantly, many techniques assume stable return distributions and correlations over time and in varying economic conditions or regimes.

For example, one of the underlying assumptions of the 60/40 model is that equities and bonds are negatively correlated and stable. The problem is that this is not always the case. From the 1960s to 2000, the correlation was largely positive, in both falling markets (such as the 1970s) and rising markets (1982 onwards).



FIGURE 9: ROLLING 3-YEARLY AUSTRALIAN EQUITY AND NOMINAL GOVERNMENT BOND RETURN CORRELATIONS (MONTHLY FREQUENCY)

Source: Milliman based upon Global Financial Data

The article 'The Myth of Diversification: Risk Factors vs. Asset Classes' by PIMCO (2010) states that:

From January 1970 to February 2008, when both the U.S. and world ex-U.S. stock markets—as represented by monthly returns for the Russell 3000 and MSCI World Ex-U.S. indexes, respectively—were up more than one standard deviation above their respective full-sample mean, the correlation between them was –17%. In contrast, when both markets were down more than one standard deviation, the correlation between them was +76%.

Also taken from the same article, the figure below shows that not only is the correlation between asset classes relatively high, but it also varies between 'calm' and 'turbulent' periods.

FIGURE 10: AVERAGE CROSS-CORRELATIONS (MARCH 1994 - DECEMBER 2009)



Source: The Myth of Diversification: Risk Factors vs. Asset Classes, PIMCO 2010

Furthermore, Straatman (2013) notes that cross-asset-class correlations have increased systematically over recent decades due to:

- Globalisation of companies, industries and markets and economies.
- Synchronised quantitative easing monetary policies.
- Financial engineering.

Therefore, we can see that the relationships between asset classes seem far from static over time and demonstrate strong regime dependence. Such dynamics are hard to allow for using the traditional approaches to portfolio construction, suggesting that new techniques should be considered.

2.2 Benefits of risk factor asset allocation

As described in Briand at al. (2009), in an ideal world, investors would be able to construct portfolios consisting of a large number of independent units generating attractive risk-adjusted returns governed by known and stable return distributions. This is, in part, the goal of risk-factor-based asset allocation.

Over recent years, risk factor investment frameworks have started to reach into the mainstream academic and practitioner literature. Not surprisingly, this is being accompanied by an increasing trend towards risk factor investing amongst professional asset management firms. As discussed in the previous section, there is now widespread agreement that many asset classes often end up being driven by the same risk factor, which undermines thinking about asset classes as relatively heterogeneous security classification structures.

Assessment of risk factors is arguably more forward-looking than the use of traditional mean-variance optimisation methods, which attempt to allocate capital to asset classes based upon distributional assumptions typically calibrated from past data. Also, by identifying the risk factors common to multiple asset classes, we can develop a much deeper understanding of how the behaviour of asset returns are linked (i.e. correlated) and therefore begin to build more robust, resilient portfolios. Considered another way, by looking at the risk factors contained in their portfolios, investors can better forecast how the portfolio may perform under different future economic conditions and understand the true underlying risk exposures.

Taken a step further, under a risk factor allocation process, it would be possible to decompose the past performance of a particular portfolio into the various, relevant risk factors. This has been completed below in Figures 11-14 for:

- Australian equities: the S&P/ASX 200 Accumulation Index
- Australian nominal government bonds
- Australian corporate bonds

FIGURE 11: EQUITY MARKET TOTAL RETURN DECOMPOSITION - ANNUAL



Source: Milliman and Innova analytics, Bloomberg data

FIGURE 12: EQUITY MARKET TOTAL RETURN DECOMPOSITION - ROLLING 4-YEAR RESULTS



12

Source: Milliman and Innova analytics, Bloomberg data



FIGURE 13: NOMINAL GOVERNMENT BOND MARKET TOTAL RETURN DECOMPOSITION - ANNUAL

Source: Milliman and Innova analytics, Bloomberg data



FIGURE 14: CORPORATE BOND MARKET TOTAL RETURN DECOMPOSITION - ANNUAL

Source: Milliman and Innova analytics, Bloomberg data

The above charts clearly show that whilst valuation risk factors are the primary driver of returns on an annual basis, they mean revert over longer periods of time, resulting in the cash-flow risk factors becoming much more important. This is evident in the reduction in volatility evident in the rolling 4-yearly equity results compared with the annual results. Over the timeframe examined, the starting P/EBITDA was very close to the subsequent long-term average. However, we would expect valuation return to have a much greater influence on returns if the starting P/EBITDA valuation were substantially above the long-term average (such as in late 2004/early 2005) or below (such as in late 2008/early 2009).

This is consistent with Shiller (2006), who suggests that when P/E has been high, subsequent 10-year returns are low, and when the P/E has been low, subsequent 10-year returns are high.

The correlations between the asset classes and risk factors over this time period are shown in the following figures.

FIGURE 15: ASSET CLASS AND RISK FACTOR CORRELATIONS. ANNUAL DATA FROM 2002 TO 2013										
	EQUITY		GOV'T. BONDS			CORP. BONDS				
Equity	1.00									
Gov't. Bonds	-0.89			1.00						
Corp. Bonds	-0.61			0.74			1.00			
	DY	SER	CER	VR	CS RP	GD RP	CD RP	RI	RCR	
Dividend Yield	1.00									
Sustainable Earnings Return	-0.03	1.00								
Cyclic Earnings Return	0.34	-0.31	1.00							
Valuation Return	0.50	-0.15	-0.78	1.00						
Credit Spread RP	0.87	-0.23	0.18	0.61	1.00					

Govt Duration RP	-0.77	-0.08	-0.32	-0.41	-0.85	1.00			
Cash Duration RP	-0.59	-0.10	-0.19	-0.38	-0.70	0.71	1.00		
Realised Inflation	-0.72	0.30	-0.04	-0.57	-0.79	0.55	0.45	1.00	
Real Cash Rate	-0.17	0.47	0.02	-0.24	-0.40	0.09	0.45	0.11	1.00

Source: Milliman and Innova analytics, Bloomberg data

The above analysis shows the misleading picture presented by the correlations at an asset class level over this period. Government and corporate bonds appear to be strongly positively correlated. However this masks the fact that the reason for this is that they share the same underlying risk factors (cash, inflation, duration), with the exception being credit spreads which were significantly negatively correlated with all of them. The negative correlation between equities and corporate bonds is similarly masking the fact that there was a significant positive correlation between credit spreads and both dividend yields and valuation returns, both of which would be expected from a fundamental perspective.

2.3 Stability of correlations

One big drawback of the traditional approaches to portfolio construction is the assumption that the relationship between asset class returns is stable both over time and under different regimes. Many authors have justified the superiority of a risk factor investment approach by pointing to the fact that historic correlations between risk factors are generally lower than those between asset classes. This includes Podkaminer (2013), Briand et al. (2009) and Jones (2011). For example, Figure 16 shows the risk premia correlations derived by Briand et al. (2009).

FIGURE 16: RISK PREMIA CORRELATIONS FROM MAY 1995 TO OCTOBER 2008											
	VALUE	SIZE	MOMENTUM	CREDIT SPREAD	HIGH YIELD SPREAD	TERM SPREAD	MERGER ARBITRAGE	CONVERTIBLE	CARRY TRADE	CURRENCY VALUE	
Value	1.00										
Size	0.11	1.00									
Momentum	-0.47	0.15	1.00								
Credit Spread	0.07	0.06	0.15	1.00							
High Yield Spread	0.06	0.26	0.20	0.56	1.00						
Term Spread	-0.05	-0.02	0.18	0.04	-0.09	1.00					
Merger Arbitrage	-0.02	0.18	0.33	0.29	0.49	-0.12	1.00				
Convertible Arbitrage	-0.02	0.18	0.52	0.25	0.39	0.17	0.44	1.00			
Carry Trade	0.00	0.10	0.35	0.41	0.45	0.08	0.37	0.58	1.00		
Currency Value	0.10	-0.04	-0.19	0.20	0.20	-0.03	0.00	-0.20	0.32	1.00	
Currency Momentum	-0.10	-0.20	-0.14	-0.13	-0.26	0.01	-0.20	-0.20	-0.01	-0.05	1.00

Source: Briand et al 2009

Returning to the analysis detailed in the article 'The Myth of Diversification: Risk Factors vs. Asset Classes' (2010), in line with the above results, it can be demonstrated that correlations between risk factors are lower than those between asset classes and also seem to be more stable across varying economic conditions. This is shown in the figure below. The risk factors considered were equity, size, value, momentum, duration, emerging market spread, mortgage spread, corporate spread, swap spread, real estate and commodities.





Source: The Myth of Diversification: Risk Factors vs. Asset Classes, PIMCO 2010

Analysis by Jones (2011) of Deutsche Bank found similar results with respect to lower correlations, where 50% of 200 pairwise correlations of long/short strategies spanning seven asset classes and three risk premia (value, carry and momentum) were negative, with only two being above +0.5. However, they also found various temporal features to historic analysis of risk premia, including:

- They exhibit significant time-variability, for example illiquidity, which tends to be highest just after the start of a period of stress.
- Regime dependence mean-reversion based strategies seem to require benign liquidity and low stress conditions to pay off.
- Systemic macro strategies tend to perform well in times of stress when positive feedback loops dominate negative ones.

2.4 What does a risk factor portfolio look like?

As mentioned previously, there is no set definition of a risk factor. We have taken 10 example factors and derived the exposure that different asset classes have to those 10 factors. The 10 factors are: economic growth, valuation, inflation, liquidity, credit, political risk, momentum, manager skill, option premium and demographic shifts.

This is by no means an exhaustive list, but helps to frame the mindset one would take when reviewing asset classes and their risk factor exposures. It should be noted that at different points in time, different assets will have more or less exposure to some of these factors, but this has not been considered for the purposes of this example.

We need to begin with two assumptions. First, we are not adjusting the allocation to asset classes due to higher ex-ante return forecasts, and second, we are not tailoring our risk factor exposures to those that best suit any particular client. We are therefore making a naïve assumption that we want to spread our risks as much as we can, irrespective of current market conditions or the needs of the client.

Given that, a portfolio constructed in a risk factor framework could look something like Figure 18:

FIGURE 18: A PORTFOLIO DIVERSIFIED BY RISK FACTORS



Asset Allocation

Long Term Risk Allocation



Source: Milliman Australia and Innova Asset Management

The asset classes used to build the portfolio in Figure 18 are very similar to the portfolio from Figure 8, but the risk allocations are very different and far more balanced. The risk-factor-based analysis has enabled greater diversification of risk.

2.5 Risk factor portfolio performance versus traditional approaches

A number of authors have carried out investigations that demonstrate that a risk-factor-based approach to portfolio construction achieves better risk-adjusted returns compared with traditional approaches. For example:

- Briand, Nielson and Stefek (2009) found that using an equal weighting across 11 style and strategy risk premia from 1995 to 2008, would have generated similar returns to traditional 60/40 portfolios but with 65% less volatility.
- Podkaminer (2013) found that a simple factor portfolio 'historically achieved a slightly higher level of return than the traditional portfolio while taking on about one quarter of the volatility'. Research by Deutsche Bank¹¹ showed that a volatility-weighted portfolio of 21 factors from 1995 to December 2011 offered higher compound returns with lower volatility than equities, world government bonds or a hedge fund composite portfolio.
- Dimitris et al. (2011) constructed and analysed risk premia portfolios using a mean-variance optimisation process subject to various types of constraints. The resulting performance of various risk premia exhibited temporal stability characteristics as well as temporal instabilities in the case of growth and volatility premia. They concluded that it is possible to improve risk-adjusted performance through the combination of value and risk-based portfolio strategies.

It should be noted, however, that most of these studies consider 'reduced risk' to mean 'reduced volatility', and therefore, while these examples provide supporting evidence of the benefits of risk factor portfolio construction, they do not tell the whole story.

2.5.1 A brief warning

In contrast to the viewpoints expressed in other papers, Idzorek et al. (2013) contested that neither an asset-class- nor a riskfactor-based approach is inherently superior to the other, even though correlations between risk factors are typically lower than those of asset classes. They concluded that, in principle, the same result could be achieved for a traditional approach (such as an asset class framework) if some typical restrictions are relaxed. For example,

- Use of the same opportunity sets: Ensure that the same underlying security sets are used for each approach, such as permitting
 investment in derivatives.
- Ensure the same portfolio construction constraints: Asset-class-based portfolios are predominantly long only, whilst risk-factorbased portfolios typically allow or require short selling in order to manufacture some risk factors.

The analysis was based upon both a mathematical investigation under an idealised world, as well as back-testing analysis over various periods of history. They demonstrated that in a perfect world where there is a one-to-one mapping of risk factors to asset classes, and in the absence of superior information, optimising across risk factors in an unconstrained way is equivalent to optimising across asset classes similarly unconstrained.

In light of this analysis, we need to be very clear about the reason for the adoption of risk-factor-based asset allocation: There appear to be no fundamental advantages based on risk/return relative to an asset class approach.

2.5.2 The advantages of the risk factor approach

While there may not be any fundamental advantages from adopting a risk-factor-based approach in terms of risk/return payoff, there are a number of important benefits which make such an approach superior to many traditional asset class methods. These benefits include:

- A more natural framework for formulating forward-looking long-term assumptions relevant to longer-term investors.
- A more transparent view into the drivers of diversification in the portfolio.
- An increased ability to understand, predict and explain the drivers of performance over different time horizons and regimes.
- An identification of the advantages of using certain short positions or derivatives as necessary to better diversify risk factors.
- The ability to use causal/Bayesian approaches to enhance the construction of resilient portfolios using modern risk management techniques, which is discussed further in the next section.

¹¹ Brad Jones, A Third Generation in Asset Allocation, January 2012.

2.6 Practical challenges of risk factor asset allocation

Unfortunately, while risk factor asset allocation addresses some of the drawbacks present with traditional approaches such as increasing investor's understanding of their true underlying risk exposures, it is not the 'silver bullet' for all investors' needs. There are well-documented challenges with risk factor asset allocation which may help to explain why this approach is not more prevalent within the industry. Podkaminer (2013) and Idzorek et al. (2013) list the following challenges facing those adopting a risk factor approach:

- Risk-factor-based asset allocation is not macro-consistent; it would not be possible for all investors to hold the same portfolio due to the frequent need for long/short positions in some assets.
- The need to determine a set containing all significant risk factors.
- Frequent portfolio rebalancing (and the associated fees and transaction costs).
- Derivation of forward-looking assumptions.
- The difficulties in capturing some risk factors.
- Use of derivatives and short positions.

To elaborate further on the last two points, since direct investment is currently unavailable for many risk factors, extreme offsetting positions or derivatives may be required to gain exposure to these risk factors. Such strategies may fall afoul of existing investment rules and portfolio constraints. Even in the absence of such constraints, we may only be able to approximately replicate certain risk factors; for others there may be no current mechanism to access them at all.

With regards to forward-looking assumptions, in the previous section we highlighted research that showed that risk factors exhibit various temporal features and regime dependence. Such characteristics are difficult to model fully using traditional statistical techniques.

Many of these challenges will no doubt be addressed as risk-factor-based investment frameworks gain traction and see wider market adoption, either through bespoke solutions or potentially the introduction of new risk-based (rather than asset-based) instruments.

2.7 Summary

Traditional allocation approaches assume that investing in a wider range of assets or asset classes will lead to a lower risk portfolio. Furthermore, it was believed that the correlation between asset classes was relatively stable. Recent experience has uncovered a number of issues with this approach, including:

- Many assets have the same underlying risk factor exposures, meaning that they are more correlated than first thought.
- The correlations between assets class exhibit temporal and regime dependence.

In addition, when considering the riskiness of various portfolios and portfolio construction techniques, volatility was considered the key measure. This may not be the only measure of risk relevant to investors.

Instead of constructing portfolios using the traditional asset class approach, risk factor portfolio construction can lead to a greater understanding of portfolio risk exposures, as risk factors tend to have lower and more stable correlations (though still exhibit some temporal/regime dependence). In Section 3 we look at causal models, such as Bayesian networks, which offer an alternative to traditional statistical methods (such as fitting to historical data) to explain asset returns and correlations. The resulting return estimates reflect the non-linear dynamics of how performance can change according to the underlying economic and business drivers. Such models provide not only a forecast of future returns but also a transparent explanation behind that forecast. In fact, causal models:

- Provide a framework for explicitly capturing the non-linear system of relationships driving return.
- Permit the transparent combination of historic data with expert judgement to derive forward-looking assumptions and facilitate a wide range of stress and scenario testing and reverse stress-testing.

3 RISK FACTOR MODELLING

It is our belief that risk factors are not always subject to stable distributions with serial independence as assumed by traditional statistical analysis. We do not believe that there is no place for such analysis; rather, we consider it to be incomplete and not capable of fully describing the dynamics seen in the real world. Consistent with our definition of a risk factor, we think that it is more useful to think of asset classes and risk factors as behaving in a certain way subject to the state of underlying causal drivers. To best model the risk and return features of individual asset classes, we need a framework that will allow for such items as:

- Mean reversion.
- Regime shifts.
- Interdependence between asset classes and common shared risk factors, such as economic growth (both actual and expected).

An example of this would be that in times of relatively benign economic conditions, investor risk appetite tends to be high and prices increase, leading to reduced and low ex-ante risk premia and low capital market volatility.

One way of trying to obtain a deeper understanding of such complex interdependencies and behaviour is to use frameworks designed and used by complex systems scientists. One such framework which can be used to enhance the modelling and understanding of risk factor asset allocation is a Bayesian network.

3.1 Bayesian networks background

A Bayesian network is a model (formally a directed acyclical graph) of the dependent relationships between causes and effects, and is made up of nodes and arcs. Each node in the network represents a 'variable', and the arcs represent the causal or influential relationships between the variables. Bayesian networks permit the modeller to capture their reasoning about how a particular consequence may arise. The model is then able to express how likely a particular outcome is, through repeated applications of Bayes' Theorem.

Over the past decade or so, computer algorithms have been developed which make the propagation of this kind of evidence much easier to achieve. Evidence can be propagated both up and down a Bayesian network to explain the likely causes of an outcome or to examine the consequences of an event occurring. It is now possible to implement quite large Bayesian network models which can propagate evidence virtually instantly. This provides a significant advantage over Monte Carlo methods for the purposes of sensitivity testing, 'what if' analyses and reverse stress testing.

3.2 Use of Bayesian networks in risk factor modelling

Similar to many risk factor portfolio analysis techniques, the first step in constructing a Bayesian network is to map the asset classes to the set of risk factors. Many authors and asset firms stop at this level and then look at the degree of linear relationship between each pair of risk factors, as captured by the covariance or correlation statistic. Whilst useful, this approach is incomplete at best and misleading at worst. This is because, as we have mentioned, risk factors also exhibit non-linear dependencies and regime activation.

Bayesian networks go beyond the mapping of asset classes to risk factors by including the most important underlying causal drivers of the risk factors. This enables the interrelationships between them to be explored at a lower causal level, with the resulting correlations between the asset class returns or risk factors arising as a by-product of these relationships. This additional layer of understanding is one of the key benefits of using a causal modelling approach to capture the behaviour of risk factors and hence asset returns.

After the asset classes have been mapped to the risk factors, a series of discussions or workshops amongst experts are carried out in order to identify, as far as possible, the causal drivers of the risk factors. Subsequent analysis is undertaken to ascertain the most important causal drivers to be included within the Bayesian network.

3.3 An example Bayesian network risk factor model

Calibrating a Bayesian network model involves some effort, with the degree of effort depending upon the nature of the system being analysed and the questions it seeks to address. It typically involves an iterative approach, in which a combination of expert judgement and analytics are required in order to examine various hypotheses to assess whether causal or correlated relationships exist amongst the various elements.

We have created a 'simple' model for a portfolio that invests in two asset classes: Australian equities and Australian bonds. We have calibrated this model as much as possible using historic data going back to 1900, and supplemented it with expert judgement where necessary. The details of this calibration are outlined in Appendix A. This includes information on the process and evidence for the resulting relationships and uncertainty that are codified in the Bayesian network model.

Unlike a traditional statistical model that requires the use of a correlation or copula to define the dependencies between equity and bond returns, a Bayesian network model is able to structurally combine the two asset classes directly. This is because the dependency structures are reflected directly in the risk factors that drive each component, such as inflation, bond yields, the state of the economy and the presence of structural imbalances. The following figure presents the complete model, showing the distribution of return on a 60/40 equity bond portfolio.

FIGURE 19: BAYESIAN NETWORK MODEL OF MONTHLY RETURNS ON A PORTFOLIO OF 60% AUSTRALIAN EQUITIES AND 40% AUSTRALIAN BONDS



At the top of the model, the full portfolio (monthly) return distribution is explicitly estimated. As can be seen from this indicative calibration, the portfolio return distribution is clearly not normal, exhibiting excess kurtosis and negative skew. These features are a direct result of the underlying causal risk factors of each asset class, such as cash rates, the states of the economy and inflation, the presence of structural imbalances and whether markets are in a normal or stressed state. Although this model only contains 11 nodes, it covers millions of individual scenarios that characterise the full range of possible outcomes.

This risk factor approach can be applied to any asset class of interest. At each stage of the modelling process, it is necessary to identify relationships (and the inherent uncertainty in them) between the risk factors across each model. For example, in deriving a model for corporate bonds, a possible approach would be to add in additional risk factors for credit spreads and default losses, which would be added to government bond yields in order to derive a corporate bond return. Credit spreads are likely to be correlated to government bond yields, which could be taken further by asking the deeper questions as to how they are related to economic growth, inflation and structural imbalance factors. It is also well-known that default losses are driven by economic growth. Deriving the nature of these causal relationships and their uncertainty is possible with sufficient data and insight.

Whilst this can be an involved process, we believe that it is both possible and critical to do so in order to understand the risk dynamics of portfolios constructed from exposure to multiple asset classes. Without such an approach, it is not possible to robustly aggregate risks across asset classes in a meaningful way that can generate insight into the true risk and return characteristics of the portfolio.

This approach is particularly valuable for modelling leveraged and derivative strategies, as it is possible to break down the exposure to the underlying causal risk factors and explicitly allow for uncertainty. This provides a clear way of understanding the strategy, its risk exposures, the degree of uncertainty and, ultimately, outcomes.

4 USE CASES

The risk factor approach allows for a more granular understanding of the risks associated with the causal drivers of return within asset classes. Building this within a framework designed to model interdependencies and capture the way in which risk changes under different regimes provides us with a unique insight when it comes to portfolio construction for particular client needs. Following this process allows us to focus on more than simply a singular measure of risk (such as volatility)—we can appreciate, model and have a greater understanding of the multi-faceted nature of risk exposures within portfolios, and tailor exposures for the needs of clients.

In the case of the end client, they will exhibit different tolerance levels to various risks (such as the risk of capital loss, inflation, liquidity, etc.). Given that the risks associated with the assets that can be used to construct a portfolio change throughout time as well, a naïve portfolio simply diversifying across risk factors (such as the one described in Section 3.3) is an incomplete way of constructing portfolios for the end user. Instead, the framework described in Sections 3 and 4 allows the portfolio manager to design a series of portfolios tailored to those varying risk factor exposures, based on the client's tolerance or capacity to be exposed to them.

Given that no asset manager has perfect foresight, the construction of an 'optimal' portfolio in an ex-ante framework is very unlikely to lead to an optimal portfolio ex-post. Approaching risk management by aiming to address the varying risk factors, nature of risk and risk appetite of clients gives the asset manager a framework to build resilient, rather than optimal, portfolios that meet clients' needs.

4.1 Client risk appetite

Risk means different things to different clients. Everyone and every entity (whether they are a group, trust or corporate) is exposed to risks of various types-inflation, injury, death, longevity, interest rates, political, economic, capital market, wages, liquidity-and they are unique to each individual. They arise from the changing interaction between a person's or group's capital resources, and the future income needed to support the required and desired levels of consumption.

To illustrate, we will look at four risk exposures:

- Risk of capital loss in any 12-month period.
- Risk of the loss of purchasing power of a portfolio, defined as a stress to inflation.
- Risk of capital loss during a recession.
- The liquidity of the portfolio, defined as the percentage of the portfolio that can be liquidated within five days.

Figure 20 defines the risk tolerances to each of these risks for three investors with different risk tolerance levels. This is broadly known as a risk appetite statement (RAS).

FIGURE 20: EXPRESS	FIGURE 20: EXPRESSIONS OF RISK TOLERANCE FOR THREE INVESTORS WITH DIFFERENT RISK TOLERANCE LEVELS											
RISK	REFERENCE	LOW TOLERANCE	MEDIUM TOLERANCE	HIGH TOLERANCE								
Loss of Capital	Return (r)	P(r<0%)<5%	P(r<-10%)<5%	P(r<-50%)								
Inflation	Annual CPI >4.5%	P(r<0%)<5%	P(r<-10%)<5%	P(r<-50%)								
Recession	GDP Growth <0%	P(r<-5%)<5%	P(r<-15%)<5%	P(r<-50%)								
Liquidity	Capital access within 5 days	100%	75%	No Restriction								

Given these four primary risks, we have assigned three levels of tolerance, or the clients' 'appetite' for those risks. These can then be combined to assess the clients' overall risk appetite, and portfolios can be built to test these constraints. Depending on the clients' circumstances, their appetite for each of these risks will vary. For example, any particular client may have a medium or high tolerance to capital loss of their financial assets in any particular year under normal economic conditions. However, if recession leads to a loss of income for them (for example, because of job loss, reduced revenues from taxes or charitable donations, or reduced revenue due to a drop in economic activity, etc.), then their tolerance to capital loss in recession may be much lower simply because their income could be much lower, i.e., they would have a reduction in income at the same time as a meaningful fall in the value of their financial assets. Therefore, loss of capital in recession is doubling up on exposure to GDP risk, which is not desirable.

These risk factor exposures and appetite can now be applied to provide a more granular, tailored portfolio on behalf of clients. We will take a stylised client example to illustrate. We assume that the client's primary concerns are liquidity and capital loss. They require 100% of their capital to be liquid and can tolerate up to a 10% loss of capital 1 in every 20 years (i.e. a 1 year probability of 5%).

Using the risk factor model described in Section 4, future return distributions were derived for 10 asset classes as at 30 June 2014. All 10 satisfied the client's liquidity requirement, and were combined to build 15 potential portfolios:

FIGURE 2	FIGURE 21: SET OF 15 POTENTIAL PORTFOLIOS COMPRISING VARIOUS EXPOSURES TO 10 DIFFERENT ASSET CLASSES										
PORTFOLIO	EQUITIES	CASH	CORPORATE BONDS	ILBS	INTERNATIONAL EQUITIES	PROPERTY	PROTECTION	TREASURY BONDS	UK FIXED INCOME	US FIXED INCOME	
1	0%	25%	15%	0%	0%	20%	30%	10%	0%	0%	
2	0%	25%	10%	0%	0%	15%	40%	10%	0%	0%	
3	0%	25%	10%	5%	0%	10%	40%	10%	0%	0%	
4	0%	35%	0%	0%	0%	5%	50%	10%	0%	0%	
5	0%	25%	5%	0%	0%	0%	60%	10%	0%	0%	
6	20%	25%	15%	20%	0%	20%	0%	0%	0%	0%	
7	40%	25%	10%	0%	0%	15%	0%	10%	0%	0%	
8	40%	25%	15%	20%	0%	0%	0%	0%	0%	0%	
9	50%	50%	0%	0%	0%	0%	0%	0%	0%	0%	
10	60%	25%	10%	0%	0%	5%	0%	0%	0%	0%	
11	0%	25%	0%	0%	25%	25%	0%	0%	0%	25%	
12	0%	25%	0%	20%	50%	0%	0%	5%	0%	0%	
13	25%	25%	25%	0%	0%	0%	0%	25%	0%	0%	
14	80%	10%	5%	0%	0%	5%	0%	0%	0%	0%	
15	90%	0%	5%	0%	0%	5%	0%	0%	0%	0%	

These 15 portfolios were then tested for the likelihood of capital loss and return:



FIGURE 22: PORTFOLIO FORECAST MEAN RETURN VERSUS PROBABILITY OF A CAPITAL LOSS GREATER THAN 10%

The above chart roughly represents the efficient frontier in the traditional sense. However, when determining the appropriate portfolio for the client, we are not looking for the best return per unit of a single risk, we are looking for the best return given a series of risks and defined maximum exposure to them. In this model, 13 of the 15 portfolios satisfy the clients' maximum loss of capital restraint (portfolios 1 to 13). Portfolios 14 and 15 both break this capital loss requirement, as the probability of loss greater than 10% in the next 12 months is greater than 5%. Therefore, if liquidity and capital loss were the only risks the client was concerned with, the best return forecast for this portfolio that satisfies the capital loss constraint would be portfolio 10.

It is unlikely, though, that clients would not need to maintain the purchasing power of their assets, and so modelling return outcomes in an inflationary environment and maintaining a positive real return is going to be important. In addition, as mentioned above, the client may have varying tolerance to loss in a recession. Given that inflation and recession are economic factors that the investment manager cannot control or avoid, these are elements that can be used to stress and scenario test the portfolios.

4.2 Stress and scenario testing

The risk factor framework gives us the ability to stress test assets and portfolios under different market conditions, due to the detailed and granular nature of the causal drivers used within the framework. As an example, we look at US 10-year treasury bonds in June 2013 and the inflationary regime at the time. Inflation is a factor that would be expected to affect most if not all asset classes if there is a regime shift. Based on capital market conditions as at June 2013, the yield on 10-year US treasuries was 2.49%, whilst spot inflation as at May 2013 was 1.4% year over year. In the absence of any forecasting ability, if we assume that the best estimate of expected future inflation is actual spot inflation, then US 10-year treasuries were paying a premium above inflation of 1.09%. In theory, if inflation in the future remained at 1.4% with absolute certainty, then there would be no reason for this premium to persist, and the capital value of the bonds would increase, thereby reducing the premium on offer. In this example, we have forecast mean return of 4.96% on nominal Treasury bonds as our base-case scenario. However, as spot inflation is not necessarily an accurate predictor of future inflation, we can use the risk factor framework to stress test inflationary scenarios to look at the risks to both the upside and downside of a shift in inflation.

FIGURE 23: SCENARIO TESTING OF INFLATIONARY REGIMES – IMPACT ON 12-MONTH FORECAST MEAN RETURN ON NOMINAL US TREASURY BONDS

TREASURY BONDS	EXPECTED INFLATION -1.5%	BASE	EXPECTED INFLATION +1.5%
Nominal Running Yield Return	2.06%	2.34%	2.93%
Capital Return	7.44%	2.62%	-7.62%
Nominal Bond Total Return	9.52%	4.96%	-4.71%

The above stress test shows the asymmetric risk profile of the bonds' potential annual payoff. If inflation in the US is expected to fall by 1.5% and enter a period of deflation, a fixed 10-year bond at 2.49% is attractive and leads to appreciation of the capital value, and a total return increase from 4.96% to 9.52%—or an increase of 4.56%. However, if inflation increases by the same 1.5%, we see a fall in capital value, with the return now shifting to -4.71%—or a change of 9.67%—more than twice the magnitude of the upside.

Without the ability to perfectly predict the future, this approach allows us to look at the risk profile of varying asset classes and determine whether we appear to be being adequately compensated for bearing the risk. Extending this to stress testing a range of potential client portfolios to assess the risk/return trade-off is a relatively easy next step.

If we take the example client from above, we already know that portfolios 14 and 15 breach the capital loss risk constraint. When tested for recession and inflation, portfolios 1 to 13 all pass this risk tolerance constraint, with 14 and 15 failing (which is unsurprising), thereby confirming portfolio 10 as offering the best return whilst meeting the risk tolerance constraints. This analysis can be undertaken throughout time as market conditions change and the risks attached to asset classes change as well. To illustrate the potential effect of this, we have chosen some historical dates and run the same stress tests. Additionally, portfolios 14 and 15 were deemed unlikely to ever pass the capital loss constraints due to their very high allocation to domestic equities and so were excluded from the tests. We would like to emphasise, though, that this process is designed to model ex-ante risk. The below simulations illustrate how this could have occurred at those periods. The framework is not simply a way to test portfolios ex-post, though it does give us a very good ex-post explanatory framework.

Portfolios 1 to 13 were tested as at February 2013, January 2012 and January 2010:

FIGURE 24: EX-ANTE MEAN RETURNS FOR PORTFOLIOS 1 THROUGH 13 AS AT FEBRUARY 2013, JANUARY 2012 AND JANUARY 2010

February 2013

PORTFOLIO	RETURN	P(R<10%)	P(R<15%) IN RECESSION	P(R<0%) UNDER INFLATION
1	2.25	0.2%	0.2%	0.2%
2	2.15	0.3%	0.3%	0.3%
3	2.11	0.3%	0.3%	0.3%
4	2.13	0.4%	0.5%	0.4%
5	1.94	0.8%	0.8%	0.8%
6	2.02	0.9%	1.1%	0.8%
7	1.90	2.8%	2.4%	2.8%
8	1.73	2.9%	1.6%	2.8%
9	1.95	3.9%	2.4%	3.7%
10	1.69	5.1%		5.0%
11	1.60	1.8%	1.6%	1.8%
12	3.74	2.1%	1.4%	2.1%
13	1.84	1.0%	1.1%	1.1%

January 2012

PORTFOLIO	RETURN	P(R<10%)	P(R<15%) IN RECESSION	P(R<0%) UNDER INFLATION
1	6.37	0.1%	0.1%	0.1%
2	6.21	0.1%	0.1%	0.0%
3	5.87	0.1%	0.1%	0.1%
4	5.50	0.4%	0.4%	0.3%
5	5.79	0.9%	0.9%	0.7%
6	6.44	0.3%	0.4%	0.3%
7	7.14	1.4%	1.6%	1.1%
8	6.45	1.6%	1.7%	1.2%
9	6.63	2.4%	2.1%	1.4%
10	7.86	2.8%	2.6%	1.7%
11	4.75	0.7%	0.9%	0.6%
12	5.96	1.6%	1.0%	1.0%
13	5.66	0.5%	0.4%	0.4%

January 2010

PORTFOLIO	RETURN	P(R<10%)	P(R<15%) IN RECESSION	P(R<0%) UNDER INFLATION
1	4.88	0.1%	0.2%	0.1%
2	4.46	0.3%	0.3%	0.2%
3	4.15	0.3%	0.3%	0.2%
4	3.65	0.6%	0.4%	0.4%
5	3.20	1.4%	0.6%	0.8%
6	4.92	0.8%	0.7%	0.4%
7	4.27	2.6%	1.8%	1.5%
8	3.44	3.0%	1.8%	1.5%
9	3.10	5.5%		3.3%
10	3.33	6.7%		4.2%
11	8.65	0.5%	0.6%	0.4%
12	6.80	1.4%	0.9%	1.0%
13	3.59	0.6%	0.9%	0.5%

In the scenarios run for 2013, portfolio 10 did not pass the capital loss risk tolerance constraint, and hit the maximum constraint for an inflationary environment. In addition, portfolio 12 was the portfolio offering the highest return whilst not breaching the constraints. In 2012, all portfolios satisfied the portfolio constraints, with the portfolio offering the highest return being portfolio 10. In 2010, both portfolio 9 and 10 would have breached the capital loss constraints, though interestingly they satisfied the inflationary constraints. However, the highest return portfolio was portfolio 11.

4.3 Portfolio construction

Traditional mean-variance optimisation procedures are designed to find the optimal mix of assets to provide the highest return per unit of risk, where risk is measured as volatility (or variance). This requires a number of long-term assumptions to be set about the future behaviour of assets, including their return and volatility, as well as static dependency assumptions, typically modelled as correlations. However, one problem with this is that no one has perfect foresight in predicting future asset behaviour. This means that portfolios that are built to be 'optimal' are only optimal under the environmental conditions inputted into the model as assumptions. When reality plays out, the portfolio is highly unlikely to be an optimal portfolio, because the behaviour of the assets in the portfolio are extremely unlikely to play out exactly as per the inputs into the model. We can therefore say that it is impossible to model an optimal portfolio without the ability to know exactly how asset classes and the investment environment will be in the future. Given that nobody has this ability, then the goal of the investment manager should now be one of building resilient portfolios, as opposed to optimal portfolios. This is where the ability to stress and scenario test portfolios under the risk factor framework translates very well into portfolio construction.

Our example client above demonstrates how the changing nature of investment markets and economic conditions lead to different portfolios offering different risk and hence return profiles. A portfolio that is managed to a low tolerance risk constraint would shift from one asset class mix to another over time, as market conditions evolve. As a result, the portfolio with the most attractive return characteristics that first meets the required risk tolerance constraints dynamically changes.

Whilst we have used a static list of 13 portfolios, the portfolio makeup that can be modelled and stress tested can potentially be dynamic and infinite. The framework provides the mechanism to determine these portfolios and stress them for multiple risk factors, depending on the clients particular risk appetite. This should lead to the construction of robust portfolios throughout time for those risks that clients care about and understand, be they risks that can largely be avoided if needed (such as capital loss or illiquidity) or those that are out of the managers' control (such as recession or inflation).

4.4 ALM for financial advice

In the financial advice framework, the accumulation of assets by an individual or family unit is designed to achieve two primary outcomes:

- 1. To provide cash/income/funding for future consumption. It can either supplement current income, or for the retiree will be the sole source of income.
- 2. To provide 'insurance' in case something goes wrong. Insurance gaps in a client's personal affairs often exist, and the gap between need and cover must be funded from savings. In the case of the retiree, personal insurance is, in general, no longer an option, so if something unforeseen occurs, funding must solely come from financial assets.

However, irrespective of where capital is invested, everyone will have future liabilities and a series of risks associated with those liabilities which are unique to each individual. They arise from the changing interaction between a person's human capital resources and the future income needed to support their required and desired levels of consumption.

The advice process now needs to focus on understanding the client's future liabilities and risks associated with them: What are the client's future liabilities, and what risks should they (and what shouldn't they) be exposed to? Not only do we need to understand how much risk a client may be able to tolerate, but we also need to assess their capacity to take on risk. Unfortunately, in most circumstances clients will need to make sacrifices and bear certain risks that they perhaps wish they didn't have to. It is rare for a client to have enough financial capital to fund all their future liabilities no matter the circumstances, so often trade-offs need to be made.

We can broadly categorise the risk factors that clients are exposed to in their daily lives into two buckets: 1) those relating to human capital (current and future income) and 2) liabilities (current and future consumption). Some examples of each are:

- Human capital: Wage inflation, employment, mortality, disability
- · Liabilities: Future consumption, goods and services inflation, longevity, liquidity, taxation

These risks play a special role in personal financial management, as their exposures are created independently of any particular investment strategy. That is, they are created as a result of living, regardless of whether an individual has any financial capital that requires management.

As individuals, we are very familiar with the above risk factors, our exposure to them, and ways in which we can mitigate them. We typically manage human-capital-related risks directly ourselves, by investing time, money and effort into education and maintaining physical health. This is particularly the case for mild stresses. However, when severe stresses are considered, most people have little risk appetite (both capacity and tolerance) to bear them. Thus they choose to transfer these risks, typically via insurance such as life, disability and health insurance. Consumption-related risks may be similarly managed through insurance strategies such as home and contents insurance to mitigate physical property risk, or annuities to manage the longevity risk during retirement. Banking solutions such as fixed-rate loans and mortgages help mitigate interest rate risk. However, many consumption-related risks cannot be so easily managed or mitigated, such as the various types of inflation risks (e.g. consumer, rental, property prices), liquidity, taxation and political risks. Some of these risks are driven by the economy and capital markets, whilst others are driven by the political system (a derivative of the social, demographic and behavioural systems).

In the advice process, it is critical to identify those liability risk factors that relate to the capital markets, either directly such as interest rates, or indirectly through, say, the economic impact on property and rental price inflation. This is because it is necessary to understand whether an individual's exposures to such risks are within their risk tolerances or not. If they are, then they can bear more of this risk through investment exposure, but if not, they will be averse to bearing additional amounts of this risk and may actively seek ways to reduce it through various insurance strategies.

Within the risk factor framework, breaking risk down to a more granular level allows a more tailored approach to risk management and portfolio construction for the individual. Assessing clients' future liabilities and the risks associated with them allows us to build more robust portfolios on behalf of the client.

5 CONCLUSION

We believe that the investment industry needs to place greater emphasis on managing risk and less on trying to find the holy grail of maximum or optimal return. In order to do this, a better approach to defining, identifying, classifying, assessing, stressing, mitigating and managing risks is needed. The traditional approach of defining risk as return volatility is divorced from the needs of clients and is the cause of the failure of optimisation approaches based upon modern portfolio theory.

In this paper we hope to have provided some insights into how a new approach to thinking about risk could help achieve better outcomes for clients. By placing the focus on the underlying risk factors rather than asset classes, it is possible to gain better insight into how risk can be managed in a way that relates directly to client objectives and their risk appetite. This moves beyond the common approaches explored by various authors around constructing portfolios out of risk factors, which still share the same mean-variance optimisation flaws of using asset classes under modern portfolio theory. Instead, by focusing on the asset and liability risk factors directly and codifying the nature and uncertainty of their interrelationships, it is possible to derive portfolio return distributions that are more intuitive and capture the complexities exhibited by capital markets.

Approaches such as Bayesian networks can then be used to stress, scenario test and reverse stress return outcomes such that risks can be directly measured and managed in accordance with the client's risk appetite statement. These can then be used to construct resilient portfolio strategies that capture the need to change holdings dynamically over time as capital market conditions and subsequent asset class risk profiles evolve. So long as the client's objectives and risk tolerances are being met, then the desire to achieve the highest return possible becomes largely irrelevant. This focus on client needs is long overdue, particularly as the bulk of financial wealth being managed starts to transition into retirement, where risk management needs become significantly more important compared with the pre-retirement accumulation phase.

6 APPENDIX A: CALIBRATING A BAYESIAN NETWORK MODEL

In this appendix, we demonstrate the use of a Bayesian network framework by creating a simple model for equity return and bond returns in the Australian market. In order to model such a portfolio, we have used relevant monthly asset return and economic data in the Australian market since 1900.

6.1 Bayesian network model for equity returns

Figure 25 shows the probability distribution of monthly equity returns in Australia since 1900.

FIGURE 25: DISTRIBUTION OF MONTHLY AUSTRALIAN EQUITY MARKET RETURNS FROM JANUARY 1900 TO DECEMBER 2013, WITH A NORMAL DISTRIBUTION CALIBRATED TO THE DATA



Source: Global Financial Data, All Ordinaries Index

Statistical analysis shows that historic monthly equity returns exhibit properties of high excess kurtosis (high peakedness and fat tails) and negative skew. As such, it is difficult to fit a 'standard' normal distribution to the equity return data using typical statistical techniques. For example, a normal distribution calibrated with the same mean and standard deviation as the historic equity return data is clearly a poor fit.

In order to better understand the distributional properties of equity returns, it may be necessary to consider whether the distribution of equity returns above is, in fact, an aggregation of a number of regime-dependent distributions, each with different statistical properties based upon the state of underlying risk factors or causal drivers. One potential candidate for such a risk factor would be the underlying state of the Australian economy, i.e., whether it is in either a stable/growth period, or a recession/ depression period.

In order to test this relationship, we have split the data into periods where the Australian economy was in recession/depression using the standard definition of two consecutive quarters of negative GDP growth. We have then further split these periods into those that coincided with a period of global war and those that did not. The basis for the latter regime is that the economy isn't functioning under a normal capitalistic system during these periods, with resource allocation being significantly more centrally commanded for production of war-based goods and services. The following graph shows historic GDP growth rates, overlaid with the various regimes.





Source: Maddison (2006) prior to 1960, Australian Bureau of Statistics since 1960

The resulting probability distributions in each of the states (stable/growth, recession/depression and war period) are shown in Figure 27 below.

FIGURE 27: DISTRIBUTION OF MONTHLY AUSTRALIAN EQUITY MARKET RETURNS FROM JANUARY 1900 TO DECEMBER 2013, SEGMENTED INTO REGIMES



Source: Milliman analysis using Global Financial Data on the All Ordinaries Index

Note: For ease of viewing, we have started the x-axis at -15%, which excludes the -42.1% return in October 1987.

FIGURE 28: SUMMARY STATISTICS OF MONTHLY RETURNS FOR THE AUSTRALIAN EQUITY MARKET, SEGMENTED BY ECONOMIC REGIME FROM JANUARY 1900 TO DECEMBER 2013				
STATE OF THE ECONOMY	ALL DATA	WAR PERIOD	RECESSION/DEPRESSION	STABLE/GROWTH
Minimum	-42.13%	-7.74%	-14.29%	-42.13%
Maximum	23.16%	6.13%	23.16%	18.83%
Mean	1.03%	0.78%	-0.68%	1.18%
Standard Deviation	3.92%	2.28%	5.52%	3.84%
Skew	-0.85	-0.77	0.40	-1.02
Excess Kurtosis	13.42	2.14	2.75	13.63

Figure 28 contains the summary statistics for each of these economic regimes as well as the data as whole.

It can be seen that when the economy is in a war state, the equity return has a slightly positive expectation, a relatively low variance, some negative skew and slight excess kurtosis. In the recession/depression state, the excess kurtosis is similar to the war period state but the distribution has a material negative mean return, some positive skew and a relatively large variance. Finally, in the stable/growth state, the distribution has a relatively high mean return, a moderate variance and negative skew, but a very high kurtosis when compared with the other states. Overall, as the Australian economy has been in the stable/growth state for a large portion of the analysis period, the distribution in that state is most like that off the entire dataset. However, it is evident that the distribution of equity returns does indeed vary depending on the underlying state of the Australian economy.

In order to construct a Bayesian network model for the overall return on equities, we have fitted distributions for each of the states of the economy. These are discussed in turn below.

6.1.1 Stable/growth state

Figure 29 below shows the probability distribution for equity returns when the economy is in the stable/growth state.



FIGURE 29: DISTRIBUTION OF MONTHLY AUSTRALIAN EQUITY MARKET RETURNS FROM JANUARY 1900 TO DECEMBER 2013, REPRESENTING A STABLE/GROWTH ECONOMIC REGIME, OVERLAID WITH A CALIBRATED NORMAL DISTRIBUTION

Source: Milliman analysis using Global Financial Data on the All Ordinaries Index Note: For ease of viewing, we have started the x-axis at -20%, which excludes the -42.1% return in October 1987.

The above chart demonstrates that even during periods of stable economic growth, monthly equity market returns do not statistically behave randomly and follow a normal distribution. Whilst behaviour broadly appears symmetric, it still exhibits excess kurtosis—high peaks and narrow shoulders. This indicates that there is more going on here. One possible interpretation is the possibility of two further modes of behaviour within this state, characterised by equivalent means but with different levels of variance. Figure 30 shows these distributions, and the mixed distribution that best fits the observed data.





Source: Milliman analysis using Global Financial Data on the All Ordinaries Index Note: The two independent regime distributions are shown, as well as the mixed regime.

The above figure clearly shows that the mixed regime represents a significantly improved fit to the actual data compared with a standard normal distribution. This mixed distribution is a weighted average of the two underlying regimes, where there is a 72% weight to regime 1 (low variance) and a 28% weight to regime 2 (high variance). The question that must now be asked is 'Why is the market exhibiting such behaviour?' One possible explanation is that an additional risk factor is causing investor behaviour to switch between these two regimes, which could perhaps be described as 'market risk environment'. This could be a function of both the level of uncertainty in future economic and capital market conditions, as well as how investors react to it in terms of their buy/sell behaviour, which could be termed 'investor risk appetite'. It is interesting to note that the chance of being in the high-risk environment is around one in every four years, which broadly correlates to half an economic cycle in length, although we have not investigated this any further.

6.1.2 Recession/depression and war period states

A similar approach has been used to fit distributions to the equity returns in each of the other states. In each of these states, the equity return distributions indicated that two significant peaks as well as skewness were present and were therefore fitted using two normal distributions with different means and variances. Once again, the data indicates the possibility that further risk factors could be identified if desired. The two resulting distributions are shown in Figures 31 and 32 below.

FIGURE 31: DISTRIBUTION OF MONTHLY AUSTRALIAN EQUITY MARKET RETURNS FROM JANUARY 1900 TO DECEMBER 2013, REPRESENTING A RECESSION/DEPRESSION ECONOMIC REGIME, AS WELL AS A BEST FIT TWO-STATE MIXED REGIME DISTRIBUTION



Source: Milliman analysis using Global Financial Data on the All Ordinaries Index

FIGURE 32: DISTRIBUTION OF MONTHLY AUSTRALIAN EQUITY MARKET RETURNS FROM JANUARY 1900 TO DECEMBER 2013, REPRESENTING A WARTIME ECONOMIC REGIME, AS WELL AS A BEST FIT TWO-STATE MIXED REGIME DISTRIBUTION



Source: Milliman analysis using Global Financial Data on the All Ordinaries Index

Clearly, the form of these distributions is not entirely clear from the data, although a two-state, market risk regime dependent model visually appears to fit the data reasonably well.

6.1.3 Extreme tail events

The above distributions deal with the most common outcomes experienced in the markets. However, there are a number of tail event outcomes that have occurred with much greater likelihood compared to what these distributions imply.

For example, the October 1987 crash occurred during a stable/growth regime, which represents an 11 standard deviation monthly event under these regime conditions. The likelihood of this event occurring statistically is 10⁻²⁹, which would happen once in every 10²⁸ years. To put this figure in context, the age of the universe is only 1.36 x 10¹⁰ years old, so it would require us waiting 10¹⁸ entire universe lifetimes to see this event happen if it were driven purely by random chance. Clearly this is absurd, from which we can conclude that these events do not follow statistically random patterns of behaviour, but rather exhibit causal Bayesian dependencies.

Although not quite as extreme, there are a number of 3-4 standard deviation events in the historic Australian equity market experience as well. Similar examples exist in other equity markets, particularly with events around the 3-6 standard deviation level, including:

- October 1929 Great Depression
- October 1987 Black Monday
- October 1997 Asian economic crisis
- March 2000 Dot-com bubble
- October 2008 Financial crisis

Crises such as these were and are caused by the presences of a combination of 'structural imbalance' factors including:

- Extremely fast-moving bull markets extending valuation levels to a tipping point threshold (e.g. 1987 and Dot-com bubbles).
- Economic imbalances.
- Political regime changes.
- Demographic imbalances.
- Fundamental consumer behaviour changes (e.g. run on a bank or currency).
- Perceived or real collapse of a systemically important financial institution.
- Significant credit and leverage in some part of the economy.

These factors differ from the normal risk dynamics that characterise markets during normal and typical stressed conditions. As a consequence of the presence of these factors, return distributions do not follow those previously outlined, but are more likely to follow significantly skewed distributions. The nature and calibration of such distributions is considerably uncertain given the lack of data (by definition), and is the subject of significant ongoing academic and industry research. For the purposes of our example model, we have assumed that returns in the presence of these factors follow an extreme value distribution as outlined in Figure 33 and Figure 34 below.

FIGURE 33: DISTRIBUTION ASSUMPTION FOR EXTREME TAIL EVENTS

FEATURE	EXTREME TAIL REGIME DISTRIBUTION
Distribution Type	Generalised Extreme Value
Order Parameter	1
Location Parameter	-10
Scale Parameter	6
Mean	-13.5
Median	-12.2
Standard Deviation	7.8

FIGURE 34: DISTRIBUTION FUNCTION FOR EXTREME TAIL EVENTS



This distribution implies that the likelihood of an event at least as bad as October 1987 occurring is around 0.4%. However, this is a conditional likelihood, as the presence of a stressed market risk environment is also necessary, which has a likelihood of around 25%. Hence, the modelled likelihood reduces to around 0.1%, which represents a 1-in-83-year event. This intuitively feels about right, given that we have only seen a single event of this magnitude once over the last 100 years.

6.1.4 Mixed distribution

We are now in a position to combine these distributions using the likelihoods of being in each state. Such distributions are functions of the multiple states in which the world may exist.

The figures below show the resulting distributions for various regimes.

FIGURE 35: FITTED DISTRIBUTIONS OF MONTHLY AUSTRALIAN EQUITY MARKET RETURNS ACROSS THREE ECONOMIC REGIMES



Combining these distributions using weights derived from the historic proportions of the Australian economy being in each state produces the distribution shown in Figure 36.

FIGURE 36: COMBINED DISTRIBUTION OF MONTHLY AUSTRALIAN EQUITY MARKET RETURNS ACROSS THREE ECONOMIC REGIMES



It can be seen that this distribution is an extremely accurate fit to the underlying historic data. However, it has yet to incorporate the tail event scenarios. In order to do this, it is necessary to determine the likelihoods of being in each of these states. This can be determined using any combination of historic experience, current indicators or forward-looking assessments. We choose to use a calibration based primarily upon history, although alternative calibrations could be readily justified depending upon the need:

- Economic state
 - 7% war
 - 7% depression/recession
 - 86% stable/growth
- Market risk environment
 - 72% normal
 - 28% stressed
- Structural imbalance factors
 - 5% present
 - 95% not-present



Note: The means of each distribution are shown as vertical lines

Figure 38 below now combines these distributions based upon their respective likelihoods into a single aggregate distribution.



This distribution now exhibits all the statistical features that we observe in the historic data, including:

FIGURE 38: COMBINED DISTRIBUTION OF MONTHLY AUSTRALIAN EQUITY MARKET RETURNS

- Broad symmetry around modal outcomes.
- Excess kurtosis.
- Negative skewness.

6.2 Bayesian network model for bond returns

Bond returns are governed completely by changes in bond yields. Hence, in order to understand the risk dynamics of bond returns, we need to look at the behaviour of interest rates. Figure 39 shows the 160-year history of Australian bond yields. Although the series is a composite of a range of bonds, it is broadly equivalent to a constant maturity index of 10 years (which has a duration of around eight years).



FIGURE 39: AUSTRALIAN 10-YEAR GOVERNMENT BOND YIELDS FROM JUNE 1857 TO JUNE 2014

Source: Global Financial Data¹²

What is remarkable about this graph is that at this extremely long-term scale, it appears that there have been only two and a half full interest rate cycles. Statistically, changes in bond yields are not stable, as they exhibit strong positive autocorrelation. Thus, a pure statistical approach to modelling bond yields as a random process is not appropriate. Instead, the challenge is to determine whether and what the underlying risk drivers of such changes might be so that we can model them causally.

The first step is to decompose bond yields into their constituent parts: cash rates and a duration risk premium. Cash rates can be further decomposed into the official RBA cash rate and a cash rate duration risk premium for investable cash, for which we have proxied using a 90-day bank accepted bill rate. The following figure shows these breakdowns since the start of the official RBA cash rate in 1976.

¹² This is a composite of the following bonds: The New South Wales 5% Debenture is used from June 1857 to December 1858, the New South Wales 5% Bond Redeemable 1888-1892 is used from January 1858 to December 1874, the New South Wales 4% Bond of 1875 Redeemable 1903-1910 from January 1875 to February 1886, the South Australia 4% Inscribed Bonds of 1886 Redeemable 1917-1936 from March 1886 to June 1917, the Australia 5.50% Registered Bonds Redeemable 1922-1927 from July 1917 to June 1922, and the Australia 5% Registered Stock of 1925-29 from July 1922 to June 1932 quoted in London and quoted in Sydney from July 1932 to July 1933. From January 1933 until December 1936, 4% bonds are used, and starting in January 1937, a weighted average of bonds of 10 years through 1940, 12 years from 1945, 20 years from June 1959 through 1980, 15 years from 1981 through 1990, and 10 years since 1991 to produce the theoretical yield on a perpetual 10-year bond.

FIGURE 40: AUSTRALIAN RBA CASH RATE, CASH RISK PREMIUM, 10-YEAR DURATION RISK PREMIUM AND 10-YEAR GOVERNMENT BOND YIELDS SINCE JUNE 1976



Source: RBA

It is clear that bond yields have largely tracked cash rates over the last 40 years or so. The duration risk premium has averaged 56 basis points over the last 20 years, but only eight basis points over the last 10. In order to earn this return in isolation, investors have had to bear around 1% in volatility risk for this. However, duration risk and cash rates are not independent of one another, but rather exhibit a well-known if relatively unstable negative correlation, as shown in Figure 41.



FIGURE 41: ROLLING THREE-YEAR CORRELATION BETWEEN AUSTRALIAN CASH AND 10-YEAR DURATION RISK PREMIUM

This negative correlation means that duration yield spreads have a strong tendency to move in the opposite direction to cash rates. From a causal modelling perspective, we have treated cash rate movements as a causal driver of duration spreads, and then overlaid a statistical process to account for the resulting uncertainty.

This brings us to monetary policy. The following figure shows the breakdown of cash rates into real cash rates and inflation.



FIGURE 42: OFFICIAL CASH RATE, REAL CASH RATE AND INFLATION SINCE JUNE 1976

Source: RBA

Over recent decades, the RBA has targeted the nominal (effectively real) cash rate to keep inflation broadly in the 2% to 3% range. Statistically, there does appear to be a positive relationship between changes in inflation and nominal cash rate changes, particularly when inflation is tracking within its targeted range (defined as a 'normal inflationary environment'). The following graph demonstrates this relationship.

FIGURE 43: QUARTERLY CHANGES IN AUSTRALIAN INFLATION AND THE OFFICIAL CASH RATE SINCE JUNE 1976, WHEN INFLATION IS IN A 'NORMAL' STATE BETWEEN 0% AND 5% P.A.



This dynamic holds only for a normal inflationary environment: No historic relationship exists when inflation is outside of these boundaries. We hypothesised that economic conditions might have an impact on the behaviour of monetary policy, but when we investigated it using historical data, we didn't find any statistically meaningful relationships. We do, however, hypothesise that monetary policy exhibits different dynamics for different inflationary states, as well as when the structural imbalances are present or not.

In the former, we expect that monetary policy will become:

- Proportionately more sensitive to changes in inflation when inflation is structurally above 5%, in order to manage inflation back down into the target range.
- Significantly less sensitive to changes in inflation during periods of deflation (inflation <0%) as cash rates start to approach their floor limit of 0%. Traditional cash-rate-focused monetary policy ceases to become effective here, which has been the experience of many countries over recent years.

When structural imbalances exist, monetary policy becomes less focused on managing inflation and more focused on managing the broader economic environment. Typically, cash rates will tend to fall with relatively high certainty, and more so when inflation is either in a normal or deflationary state. Such monetary policy behaviour has been seen during the recent global financial crisis, where cash rates were slashed very quickly both in Australia and in many other developed markets. Thus, even under this relatively simplistic yet intuitive view of monetary policy behaviour, the bond market can exhibit significant non-linear behaviour.

The following figure shows the dynamics of the bond market under this model across a range of inflation and structural imbalance states.

FIGURE 44: AUSTRALIAN BOND MARKET BAYESIAN NETWORK MODEL DYNAMICS



Note: There are three scenarios where no structural imbalance factors are present, when inflation is in a high (green), normal (blue) and deflationary (orange) state and one scenario where structural imbalances are present in a normal inflationary state (purple).

The above bond model clearly demonstrates risk dynamics conditional upon the state of inflation and the presence or otherwise of structural imbalance factors. These factors can either be observed or assessed such that the resulting distribution is a mixture across all of these.

6.3 Combined Bayesian model

This risk factor approach can be applied to any asset class of interest. At each stage of the modelling process, it is necessary to identify relationships and the inherent uncertainty in them between the risk factors across each model. For example, in deriving a model for corporate bonds, a possible approach would be to add in additional risk factors for credit spreads and default losses, which would be added to government bond yields in order to derive a corporate bond return. Credit spreads have a tendency to be negatively correlated to government bond yields reflecting capital flight to quality scenarios, which could be taken further by asking the deeper questions as to how they are related to economic growth, inflation and structural imbalance factors. It is also well known that default losses are driven by economic growth. Deriving the nature of these causal relationships would be possible with sufficient data and insight.

Whilst this can be a difficult process, we believe that it is both possible and critical to do so in order to understand the risk dynamics of portfolios constructed from exposure to multiple asset classes. Without such an approach, it is not possible to robustly aggregate risks across asset classes in a meaningful way that can generate insight into the true risk and return characteristics of the portfolio.

For the purposes of this paper, we have limited portfolios to equity and bond asset classes. Unlike a traditional statistical model that requires the use of a correlation or copula to define the dependencies between equity and bond returns, a Bayesian network model is simply able to structurally combine the two models directly without this need. This is because the dependency structures are reflected directly in the risk factors that drive each component. The following figure presents the combined model, with the addition of a portfolio return reflecting a 60/40 equity bond mix.

FIGURE 45: COMPLETE BAYESIAN NETWORK MODEL FOR AUSTRALIAN EQUITIES AND BONDS



The only additional relationship we have captured in this model is a weak negative relationship between bond yields and equity returns, reflecting the fact that they are a fundamental driver of equity valuation levels. At the top of the model, the full portfolio return distribution is explicitly estimated. As can be seen from this indicative calibration, the portfolio return distribution is clearly not normal, exhibiting excess kurtosis and negative skew.

In summary, the benefits of this approach are:

- Asset class risk factor dependencies are modelled explicitly, enabling a richer understanding of the full distribution of return outcomes.
- Uncertainty estimates are explicit, and reflect appropriate combinations of both expert judgement and statistical robustness where data is available.
- Complex non-linear regime-based dependencies can be easily incorporated.

7 APPENDIX B: EX-POST ANALYSIS

The risk factor approach provides us with a useful framework to examine previous market conditions and hence frame our forwardlooking thinking and stress testing of portfolios. It can also be used to test and question many of the common 'rules of thumb' that exist in the investment management world. One of these that seems to have arisen since the global financial crises of 2008 is that 'When markets turn bad, all correlations go to 1'.

As an example of how the risk factor framework can provide us with a useful ex-post explanatory framework and test common beliefs, we will look at the 'Tech Wreck' of the early 2000s. As with the fall of 1987, this was primarily driven by valuation factors. However, unlike 1987, there was an extreme concentration of overvaluation amongst all companies that were Internet- or technology-related, and in particular these were prolific in the United States. There was a level of spill-over to other areas of the market, with some sectors trading above their historical valuation levels, but it was primarily concentrated in the technology-related stocks. That being the case, under a risk factor framework we would not expect other asset classes, market sectors or investment markets that did not have the same extreme valuation misbalance to act in the same way or to the same magnitude. This is indeed what we saw.

If we begin by looking at the S&P 500, the magnitude of the valuation sell-off can be seen in Figure 46 below. In 2002 alone, the index fell 32.94% from 4 January 2002 to 2 October 2002. From 1 September 2000 to 9 October 2002, the total market fall was 47.4%.



This market fall, covering a two-year period, was concentrated in the technology sector. If we look at the Australian market, the technology-related sector was a much smaller component in comparison to the United States, and so the valuation risk factor should not have had such an influence on the result. In fact, in contrast to the United States, both 2000 and 2001 were positive years for the ASX 200 Total Return index. It was not until 2002 that we saw a fall. From 7 March 2002 to 13 March 2003, the total return index fell 24.32%.

FIGURE 47: S&P/ASX200 INDEX FROM 2000 TO 2003



S&P/ASX 200 - TOT RETURN IND

Again, this was primarily driven by a change in the valuation return component of the market: It was not driven by a fall in GDP growth, overall corporate earnings, a spike in Inflation, a sudden shift in credit regime or other causal drivers of return.

To examine this further, we can look at asset classes that were not exposed to extended valuations, but were exposed to other common macro-economic risk factors and examine the result of the Tech Wreck on their return. If we look at two other asset classes, Australian bonds (as represented by the UBS Composite) and listed property (represented by the ASX 200 A-REIT index) we do not see any fall at all-over the 2000-2003 period, returns were positive.

FIGURE 48: UBS AUSTRALIA COMPOSITE ALL MATURITIES BOND INDEX INDEX FROM 2000 TO 2003



- UBS AU COMPOSITE ALL MATURITIES - TOT RETURN IND





S&P/ASX 200 A-REIT - TOT RETURN IND

When compared together, the difference becomes quite stark, as can be seen in the 'Growth of \$10,000' chart below:

FIGURE 50: GROWTH OF \$10,000 INVESTED FROM 31 MARCH 2000 TO 31 DECEMBER 2003

\$18,000 \$16,000 \$14,000 S&P ASX 200 TR \$12,000 S&P ASX 200 A-REIT TR S&P 500 TR \$10.000 USB Composite TR \$8,000 \$6,000 \$4,000 \$2,000 \$-3/31/2000 3/31/2001 3/31/2002 3/31/2003

GROWTH OF \$10,000

As we can see, there was not a common risk factor that drove the Tech Wreck market crash; it was instead an isolated factor based on equity market valuations in one particular sector. This is in contrast to the 2008 market crash, where a number of common risk factors were the causal drivers of returns across a range of asset markets. Amongst equity markets, corporate earnings were well above trend in 2007, and growing. This means that, if one were to simply compare market prices with current earnings, the market valuation did not look overly stretched. However, if one were to compare prices with a more normalised figure for earnings, equity markets around the world and across sectors were trading at valuation premiums.

46

We saw the same thing in listed property markets, with the S&P ASX 200 A-REIT index price to NTA trading more than two standard deviations above the long-term average. Credit yields were trading at historic lows within the bond market, in particular within the high-yield space (sub-investment grade). In addition, there was the systemic risk of entering into a stressed credit environment. A stressed credit environment represents a different regime in which assets exist, and we would expect markets to respond accordingly. As a regime, the credit environment feeds through to almost all investible listed asset classes. That being the case, within a risk factor framework we would expect any shift in that regime to affect all asset classes, not just a small number in isolation. This is indeed what we saw occur, with the environment changing from a benign credit environment to one of extreme stress. Combine this with over-valuation across many asset classes and we get 2008 as a result.

We are not suggesting that a risk factor framework could predict the market environment of 2008-that is not what we are trying to achieve. What the framework can do is provide a useful approach to stress or scenario testing looking forward. The granular approach to risk factor modelling allows us to either concentrate on isolated factors that are trading away from historic norms, or stress regimes that can affect all asset classes across the investment spectrum.

8 ACKNOWLEDGEMENTS

The authors would like to thank Josh Corrigan who contributed to the production of this research report. Without his help much of this research report would not have been possible.

9 REFERENCES

Asl F., Etula E., 2012, 'Advancing Strategic Asset Allocation in a Multi-Factor World', The Journal of Portfolio Management, Fall 2012, Vol 39, Number 1.

Bhansali V., Davis J., Rennison G., Hsu J., Li F., 'The Risk in Risk Parity: A Factor-Based Analysis of Asset Based Risk Parity', The Journal of Investing, Fall 2012, Vol 21, Number 3

Briand R., Nielsen F., Stefek D., 2009, 'Portfolio of Risk Premia: A New Approach to Diversification', MSCI Barra Research Insights, January 2009.

Dimitris M., Briand R., Urwin R., 2011, 'Harvesting Risk Premia with Strategy Indices', MSCI Research Insight, Sep-2011

Idzorek T., Kowara M., 2013, 'Factor-Based Asset Allocation vs. Asset-Class-Based Asset Allocation', Financial Analyst Journal, Vol 69, Number 3, CFA Institute

Jones B., 2011, 'Third Generation Asset Allocation', Deutsche Bank, The Asia Investor Letter, November 2011

Jones B., 2012, 'A Third Generation in Asset Allocation', Presentation, January 2012

Maddison, A., 2006, 'Western Offshoots Australia, New Zealand, Canada and the United States' in the World Economy: Vol 1: A Millenial Perspective and Vol 2: Historical Statistics, OECD Publishing, http://dx.doi.org/ 10.1787/9789264022621-15-en

Nagy Z., 2010, 'Report on Active Management of the Norwegian Government Pension Fund – Norway', https://www.regjeringen. no/globalassets/upload/fin/statens-pensjonsfond/2011/riskmetrics_spn.pdf

O'Neill J., Stupnytska a., Wrisdale J., 2013, 'A Simple Alternative Asset Allocation Framework', Goldman Sachs Asset Management, Monthly Insights, March 2013

Parikh S., 2012, 'Asset Allocation Focus', PIMCO, Nov 2012

PIMCO, 2010, 'The Myth of Diversification: Risk Factors vs. Asset Classes', PIMCO

Podkaminer E., 2013, 'Risk Factors as Building Blocks for Portfolio Diversification', Investment Risk and Performance, CFA Institute

Ransenberg D., Hodges P., and Hunt A., 2012, 'LDI in a Risk Factor Framework', The Journal of Investing, Summer 2012, Vol. 21, No. 2: pp. 105-116

Rohde L., Dengsoe C., 2010, 'Higher Pensions and Less Risk: Innovation at Denmark's ATP Pension Plan', Rotman International Journal of Pension Management, Vol 3, Issue 2, Fall 2010

Shiller, R. J., 2006, 'Irrational Exuberance Revisited', CFA Institute Conference Proceedings Quarterly, Vol. 23, No. 3 (September 2006): 16-25

Straatman J., 2013, Innovations in Asset Allocation and Risk Management after the Crisis', CFA Institute, March 2013



ABOUT MILLIMAN

Milliman is among the world's largest providers of actuarial and related products and services. The firm has consulting practices in life insurance and financial services, property & casualty insurance, healthcare, and employee benefits. Founded in 1947, Milliman is an independent firm with offices in major cities around the globe.

MILLIMAN IN EUROPE

Milliman maintains a strong and growing presence in Europe with 250 professional consultants serving clients from offices in Amsterdam, Brussels, Bucharest, Dublin, Dusseldorf, London, Madrid, Milan, Munich, Paris, Stockholm, Warsaw and Zurich.

milliman.com



Milliman does not certify the information in this update, nor does it guarantee the accuracy and completeness of such information. Use of such information is voluntary and should not be relied upon unless an independent review of its accuracy and completeness has been performed. Materials may not be reproduced without the express consent of Milliman.

Copyright © 2015 Milliman, Inc. All Rights Reserved.

11 Old Jewry London, EC2R 8DU United Kingdom Tel +44 (0)20 7847 1500 Fax +44 (0)20 7847 1501