Profile to Portfolio: Where is the Missing Link?

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Abstract

This paper focuses on comparing reproducible methodologies to map an investor risk profile into portfolios, products, and solutions in a suitable manner. This study is premised on the assumption that financial advisors have access to valid measures of an individual's tolerance to take investment risk or aggregate investor risk profile, and measures of the riskiness of products and portfolios of products. We compared three methodologies from the academic literature or regulators against investment alternatives we constructed. The alternatives were a range of 14 efficient portfolios using long-term indices in the United States, Canada, the United Kingdom, and Australia. Seven were based on an equal distribution of risk (i.e., the standard deviation increased equally between the seven portfolios), and seven portfolios where the percentage return of each portfolio increased by the same amount between each portfolio. The portfolios distributed by risk were discarded in favour of those distributed by return, and these were then mapped to determine the risk level of the investor they were considered suitable for based on the three methodologies. It was determined that (a) behavioural expectation and exposure to equities is a valid heuristic but insufficient to scale to the wide variety of portfolios and products, use of leverage, and other factors in the marketplace; (b) rolling standard deviation measures can lead to significantly understated assessments of risk in some periods; and (c) the VaR calculation is recognized in multiple sources as the preferred methodology to align investor concerns of drop in the value of their portfolio to the actual products, but like standard deviation, it is highly impacted by the period utilized. After altering two methodologies (i.e., MIFiD-II and RiskCAT) based on altered duration of data and scaling, respectively, we found that the four methodologies tested agreed with less than one risk band variance and an average correlation of 0.95 to 0.97.

Recommended Citation

Brayman, S., Potts, N., Brayman, K., & Komissarov, Y. (2023). Profile to portfolio: Where is the missing link? Financial Services Review, 31(4), 246-265.

Introduction

Suitability issues are the primary area of complaint by investors to regulators or Ombudsman services in most developed markets (Brayman et al, 2015). This paper was conceptualized to gain a better understanding of why there is so much difficulty in mapping

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investors to suitable products. There are challenges in “Knowing Your Client” but scientifically validated tools exist (although they are not always used by the advisor marketplace). Portfolio managers have a wide variety of analytical tools that they can measure variants of the risk of products and portfolios, even if they are difficult to explain to investors. But by what mechanism do many advisors think an “average investor” should have a 50% fixed income and 50% equity portfolio when it is known that only 61% of American’s even own equities?

In fairness, we know that there are multiple constraints and frameworks that advisors must work within and there are systemic and demographic factors at play. Income, education, age, marital status, and race all have strong correlations to whether someone owns equities. Of households with under $40,000 of income only 29% own equities while 84% of Americans with family incomes greater than $100,000 own equities. Lack of equities is less about risk suitability than fundability. Based on licencing, advisors may be constrained to measure investment product risk, product by product whereas other investors can determine suitability at a portfolio level. In practice this means a balanced mutual fund might contain some amount of large cap, small cap, international and emerging markets and be deemed suitable for a client, but if the advisor tried to create the identical allocation using separate ETFs for each asset class, they might be precluded from selling the small cap or emerging markets as being unsuitable/too risky. In some cases, regulators might allow measuring suitability at a portfolio level if the advisor/firm has the technology systems and processes to do so – which is far more complicated than monitoring the risk of individual products. As well clients may not have their entire portfolio with a single advisor – so certificates of deposit at a bank and equity investments with an investment specialist. Can firms monitor assets “held away” and balance to the overall portfolio suitable for the client or do they need to ensure the client has sufficient defensive assets held with them?

Clearly advisors have a formidable task and financial advisors who, by definition, need to look at the holistic position of the client and ensure that solutions are in the investors best interest may need to be very creative to do this and ensure they comply with all the requirements of their compliance department and the regulator. In this paper we are addressing the problem from the financial planning perspective.

Significant research has explored how to measure an investor’s tolerance for risk or willingness to take on risk. Limited research has evaluated how advisors combine various investor behavioural and planning factors to arrive at a "risk profile" for an investor (i.e., how do financial advisors adjust for time horizon, risk capacity, etc.). Assuming a financial advisor does so, they are then expected to be able to map risk-tolerance/profile scores to suitable product solutions or portfolios that they intend to recommend.

This “mapping” stage requires that there is an acceptable methodology for measuring investment risk related to products as well as relating this investment risk measure back to the profile of the investor. A search of the literature and common practices in the financial advisory field illustrates that there are many possible approaches but little consensus on best practice. This diversity in methodologies exists in part because of the wide variety of considerations—from investor expectations to the nature of the returns in a specific market to the unique features of individual products (e.g., leverage, downside protection, currency), which can be even more obscured with current forms of engineered products. The purpose of this paper is to review approaches to mapping an investor’s risk profile to an investment solution, with the objective of identifying best practices that can be utilized by financial advisors.

Literature Review

While there is no universal consensus in the literature, there appear to be four key components of a risk profile: risk capacity, risk need, time horizon, and behavioural risk tolerance (Hubble et al., 2020). Because short-term volatility does not necessarily equate with long-term underperformance, investment horizon should be more prioritised in mapping risk tolerance to investment portfolios (Hanna & Chen, 1998). Droms and Strauss (2003) advocated for a more qualitative, personalised, and intuitive approach to portfolio selection, still based on a risk profile and investment horizon, but mainly based on the rough characteristics of asset classes and their ‘appropriateness’ in terms of trade-offs. This is still a commonly practised approach, but relatively ad-hoc in its justifications.

Investors perceive risk as negative, in terms of the possibility of underperformance, financial loss, and/or inability to meet financial goals. Swisher and Kasten (2005) asked what the minimum level of return that is ‘acceptable’ to the investor is and use Minimum Acceptable Return (MAR) as the boundary at which to measure downside risk, then optimise a portfolio based on similar principles of MVO, but in what they call Downside Risk Optimisation (DRO). Grable (2008) proposed an alternative based on a multiplicative model of risk profile (from risk profile, risk capacity and time horizon). Grable called this RiskCAT, with the result being a RPS (i.e., score). With this model, an investment risk index is generated with a Beta index of 1 for a 75% U.S. large cap and 25% U.S. small cap portfolio. A VaR (Value at Risk) calculation is then used to map to corresponding RPS. Grable also noted that it may be possible to map the RPS to the efficient frontier.

Davey (2015) outlined a detailed relationship between investor expectations for the percentage of growth assets in a portfolio and also largest drops in value they expect as they relate to risk tolerance. Davey based observations on data from 80,000 respondents to the FinaMetrica risk-tolerance assessment. Davey back tested the model against portfolios and historical data to confirm the alignment with the largest historical market declines.

Regulators have approached the mapping issue differently. In the European Union, regulations went into effect in 2018, in which the European Securities and Markets Authority prescribed a method to calculate the risk on investment products and portfolios, which were then rated at one of seven risk levels. The method at its simplest is a standard deviation based on the five-year monthly volatility of a fund annualized, or in the absence of a history, the expectation based on representative asset classes. Additionally, financial advisors were provided guidelines on how to consider risk outside normal market behaviour based on guarantees, counter-party risk, embedded leverage, currency, and other factors.

Some have argued that a risk parity approach should be used to build an optimal portfolio using the risk factors of the investments with no consideration for their associated returns. Haesen et al. (2017) attempted to balance the risk parity approach with the mean-variance model using Black-Litterman in a multi-step process. Other ways to map investor risk to portfolio risk include (a) shortfall analysis, (b) expected utility (i.e., how much value the investor expects the investment will provide, which is different from the statistically logical choice), and (c) relative risk aversion (Hanna & Chen, 1998). Several models take a risk number and use this as a parameter in a risk model calculation that produces a given return, then map it on to the efficient frontier, or ad-hoc match it to a set of portfolios.

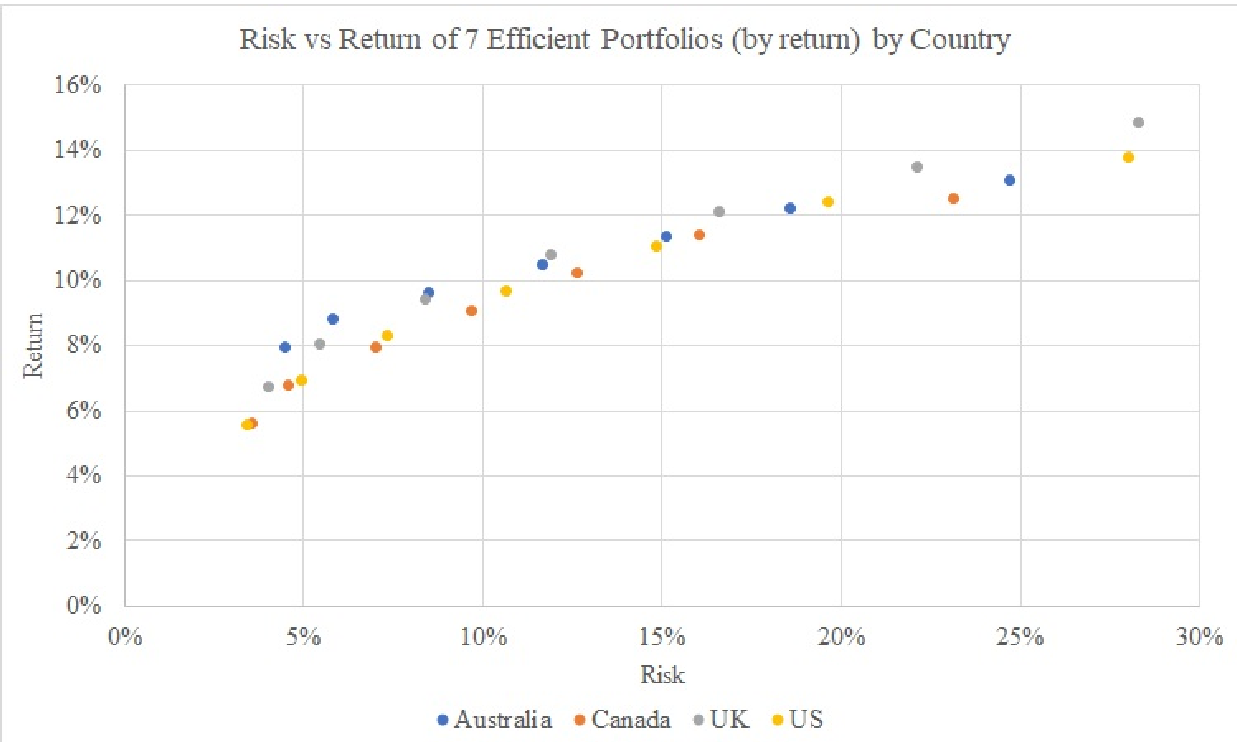
Models that use risk in calculations do so in different ways. For example, some researchers have used a function that weights risk according to a subjective aversion to produce a spectral risk measure, such as the risk aversion parameter in the Black-Litterman model and related models such as in Haesen et al. (2017). Others have equated risk scores with the Beta value in a VaR calculation for the maximum level of risk. With this approach, investor preferences for return and risk described in a spectral utility function are then mapped mathematically onto the efficient frontier. Finally, other approaches to selecting optimal portfolios based on risk may not consider an investor’s risk profile at all.

Methods

The objective of this study was to evaluate multiple replicable methodologies for mapping or linking from an investor’s risk profile to product solutions and discover if there is any commonality in the outcomes that would indicate a consensus or ‘best practice’. In the same way financial advisors would or should question tools for measuring tolerance for risk or a risk profile to determine if they give materially different measures for the same investor, or question statistical measures of risk of a product if one measure says a product is low risk and another say the same product is high risk, there should be some degree of consistent outcome when financial advisors map the risk of a product to the profile of an investor. If there is no consensus, can this be reasonably explained and resolved?

In this study, we used four existing mapping methodologies (or refinements thereof) to test if there was any material difference in the results. For each methodology, we mapped a series of efficient portfolios using long term historical data, looking at four markets/countries: Australia, Canada, the United Kingdom, and the United States. We explored two methods for distributing portfolios along the efficient frontier, based on even increments of the standard deviation or even increments of expected returns. In total, we examined 14 portfolios for each of the four countries using four methodologies. After consideration, we discarded seven portfolios based on an equal distribution of risk and utilized the seven using an equal distribution of return. (See Figure 1.)

Figure 1. Seven Efficient Frontiers with Even Distribution Based on Expected Return



The remainder of this paper is focused on answering the following question: Do the four methodologies map these seven portfolios into the same or similar risk bands for investors?

Although FinaMetrica/Morningstar have a proprietary psychometric stated-preference risk tolerance test, and the Grable-Lytton test (Grable, Lytton, 1998) is a well-documented and cited stated-preference psychometric test mentioned in the RiskCAT paper, the respective mapping methodologies are independent, simply assuming the use of a valid risk tolerance assessment. In the MIFiD-II Final Report (ESMA, 2018), although guidance is provided by the regulator on accessing an investor risk profile, there is no prescribed risk-tolerance methodology. We assume valid and reliable tests would generally categorize an investor similarly (i.e., a risk averse investor should be discernible in any valid and reliable methodology and a high-risk taking investor should be equally as discernible), hence the individual risk tolerance assessment is outside of the scope of this paper. Instead, we use the mapping methodologies to categorize the seven portfolios/products to determine if they are considered suitable for the same risk level of investors.

Mapping Methodologies

The following mapping methodologies were tested:

A mapping system based on Davey (2015) using available FinaMetrica data of "behavioural expectation" of how much equity/growth investments a consumer "expects to hold" in their portfolio.

A secondary mapping methodology based on Davey (2015) data of "behavioural expectation" of the largest drop in value a consumer would expect in their portfolio (i.e., downside risk/VaR).

A mapping approach based on the standard deviations of portfolio/products based on five-year historical data, which is more in line with stated requirements by some regulators (MIFiD-II in Europe in particular) when measuring product risk.

A mapping methodology based on RiskCAT, outlined by Grable (2008) that relates an overall profile score to a product risk index pegged against U.S. large and small cap equities using VaR.

To allow an effective comparison between approaches we defined a common framing or distribution of risk profiles. Both FinaMetrica and MIFiD-II utilize seven risk bands, so we used this as the basis. When evaluating the results, it is important to note the following scoring methodologies:

FinaMetrica uses a 0 to 100 risk-tolerance score, which is mapped into seven risk profile groupings based on the standard deviation of score distribution.

MIFiD-II uses seven risk bands defined by prescribed thresholds of standard deviations of the products.

RiskCAT uses a 0 to 2.5 scale which we mapped into seven evenly distributed bands for consistency.

Risk tolerance in the population is accepted as being normally distribution (like I.Q.). In most profiling approaches this attribute may then be constrained or reduced by other factors when arriving at a final risk profile. As an example, short time horizons or reduced risk capacity might indicate that a high tolerance investor should still take lower levels of risk when investing, as they do not have the time to recover or other resources to rely on in the event of bad outcomes. For this study, we considered the investor as "unconstrained".

For each methodology we took the seven benchmark portfolios defined for each market and compared which risk band each methodology assigns them to. We acknowledge that in doing this that although each methodology may have seven bands, the breakpoints for each band may vary since the FinaMetrica approach is distributed by population, MIFiD-II by a product risk range, and RiskCAT scores evenly.

Analysis of Portfolios by Risk or Return

We used long-term asset allocation data from four countries (i.e., Australia, Canada, the United Kingdom, and the United States). Data varied from 44 to 73 years ending in 2022. We used five asset classes for each country: (a) cash, (b) domestic fixed income, (c) domestic large cap, (d) international equity, and (e) emerging markets. Due to short data collection histories, domestic small cap equities were not utilized (see Appendix 1 for details) other than in the United States for the calculation of the RiskCAT Index.

Using these data, we used two approaches to generate a series of seven portfolios along the efficient frontier, based on even risk distribution (Figure 2) and even return distributions (Figure 1 above). For portfolios with an even risk distribution, we defined the Risk Range for each country as difference between the standard deviation (SD) of the most volatile asset class (Emerging Markets) and the SD of the lowest risk asset class (Cash). Similarly, the Return Range was difference between the highest return asset class (Emerging Markets) and lowest return asset class (Cash).

Target risks levels for the seven efficient portfolios distributed evenly by levels of risk were generated by taking standard deviation of Cash plus Risk Range/14 for Portfolio 1, then adding Risk Range/7 for Portfolios 2 to 7. As an example, for the U.S. (Appendix 1) Cash has standard deviation of +/- 3.82 while Emerging Markets have a standard deviation of 33.11, so:

SD Portfolio 1 = 3.82 + (33.11-3.82)/14 = 5.91

SD Portfolio 2 = 5.91 + (33.11-3.82)/7 = 10.1, etc.

For each of the Target Risks we solved for the efficient portfolio and resulting asset allocation, expected return, standard deviation, and Value at Risk. We repeated the process but with evenly distributed returns by calculating the Return Range as return of the highest performing asset class (Emerging Markets) and the lowest return asset class (Cash).

We then evaluated the efficacy of each distribution to ensure reasonableness in application.

Behavioral Expectations of Equity Exposure and Maximum Decline in Value

The FinaMetrica risk tolerance questionnaire has question data that can map risk-tolerance scores to both an expected percentage of growth assets (methodology #1) and a largest potential decline in value of investments before investors become uncomfortable (methodology #2) (Davey, 2015). In the case of equity/growth exposure, this study used a question about the expectation of high risk, medium risk, and low risk investments that investors expected in their portfolio. Although Davey’s estimate of 100%, 50%, and 0% equities/growth for the three risk categories respectively is reasonable, expectation is not advice and a different assumption (e.g., 60/40 is medium risk) would skew the results to higher equity content across expectation categories. Davey found little statistical variation by country and therefore generalized across countries.

In this study, we compared the percentage of growth assets for each of the seven portfolios (distributed by return) for the four countries by combining the proportions of recommended domestic equity, international equity, and emerging markets and mapping them to the risk band defined by Davey (methodology #1). We then compared the VaR of each of the seven portfolios above for the four countries against the expected downside expectation for the seven risk bands (methodology #2). Davey used an aggressive 3.5x standard deviation factor which was replicated in this study.

Five-year Monthly Standard Deviations and MIFiD-II Mapping

MIFiD-II regulation outlined a range of standard deviation intervals and their respective mapping into seven risk bands. These are shown in Table 1. As previously outlined, in this study, volatility was calculated as the five-year monthly standard deviation, annualized as follows (methodology #3):

Using asset allocations of the seven efficient portfolios distributed by even returns for each country, and the representative five-year monthly index data, we calculated the standard deviation as prescribed by MIFiD-II regulations in Europe.

MIFiD-II also prescribes a method for mapping products based on the standard deviation into one of seven risk bands (see Table 1). Using the MIFiD-II mapping, we tested to see if our efficient portfolios map into the seven prescribed risk bands or are otherwise distributed.

Because of the inconsistent results of rolling five-year standard deviations, we also used the same long-term standard deviations as were used elsewhere and the prescribed bands outlined by MIFiD-II.

Table 1. MIFiD-II Mapping Rules Based on Standard Deviation Intervals

Risk Class	Volatility Intervals	
	Equal or above	Less than
1	0%	0.5%
2	0.5%	2%
3	2%	5%
4	5%	10%
5	10%	15%
6	15%	25%
7	25%	

RiskCAT Methodology and VaR

RiskCAT was designed as a methodology by Grable (2008) that was intended to provide a robust approach for calculating a risk profile for an investor/portfolio. The method is based on a multiplicative algorithm that combines risk tolerance, risk capacity, and time horizon to arrive at a profile score. Grable proposed a method to map from a RiskCAT score into a multiple of an index based on 75% U.S. large cap and 25% U.S. small cap equities, which was linked to a RiskCAT score of 1.0 of a potential 2.5. Because the scale assumes a 2.5 return multiple of a 100% equity portfolio, it seems "dated" and linked to beliefs predating our planning understanding of the difficulty for financial advisors to consistently and materially outperform index/ETF returns, we also ran RiskCAT rescaled to a 1.25x market as the upper threshold.

Results and Analysis

Efficient Frontier Portfolios Using Long Term History

For each of the four primary markets considered, we created the longest series of historical data possible for five asset classes: (a) cash, (b) domestic fixed income, (c) domestic large cap, (d) international equity, and (e) emerging markets. We did not include small cap equities in the portfolio construction as there was insufficient data history in countries outside the United States. Data from U.S. Small Caps is shown in Appendix 1 as it remains material to the Beta calculation for the RiskCAT methodology.

Observations on the Efficient Frontier

When the portfolios were distributed by even levels of risk, we ended up with portfolios that were much more heavily equity biased. As seen in Figure 3, the portfolios were allocated 100% in equities by Portfolio 4 for Canada and the United States (1 being the least risky and 7 the riskiest) and Portfolio 5 for Australia. The efficient frontier (Figure 2) of portfolios distributed evenly by risk is displayed based on the arithmetic mean which was used in the efficient frontier calc.

Figure 2. Seven Efficient Portfolios Evenly Distributed by Increments of Risk

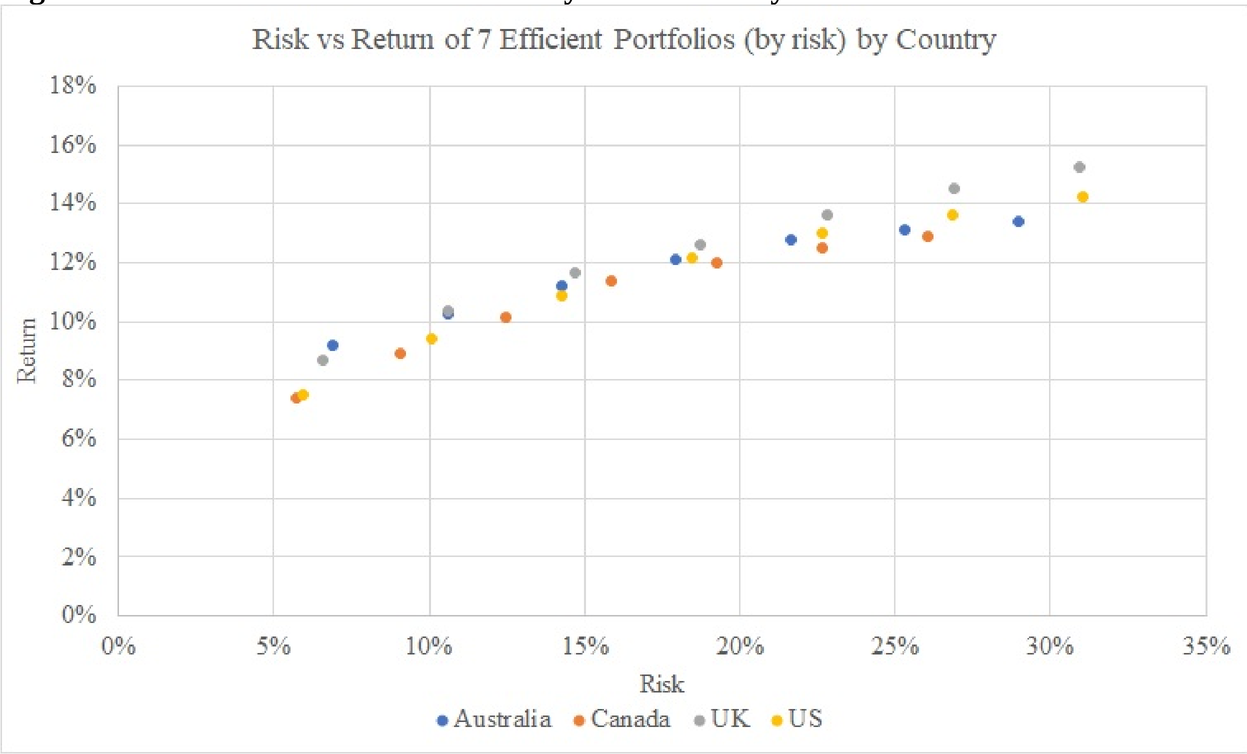
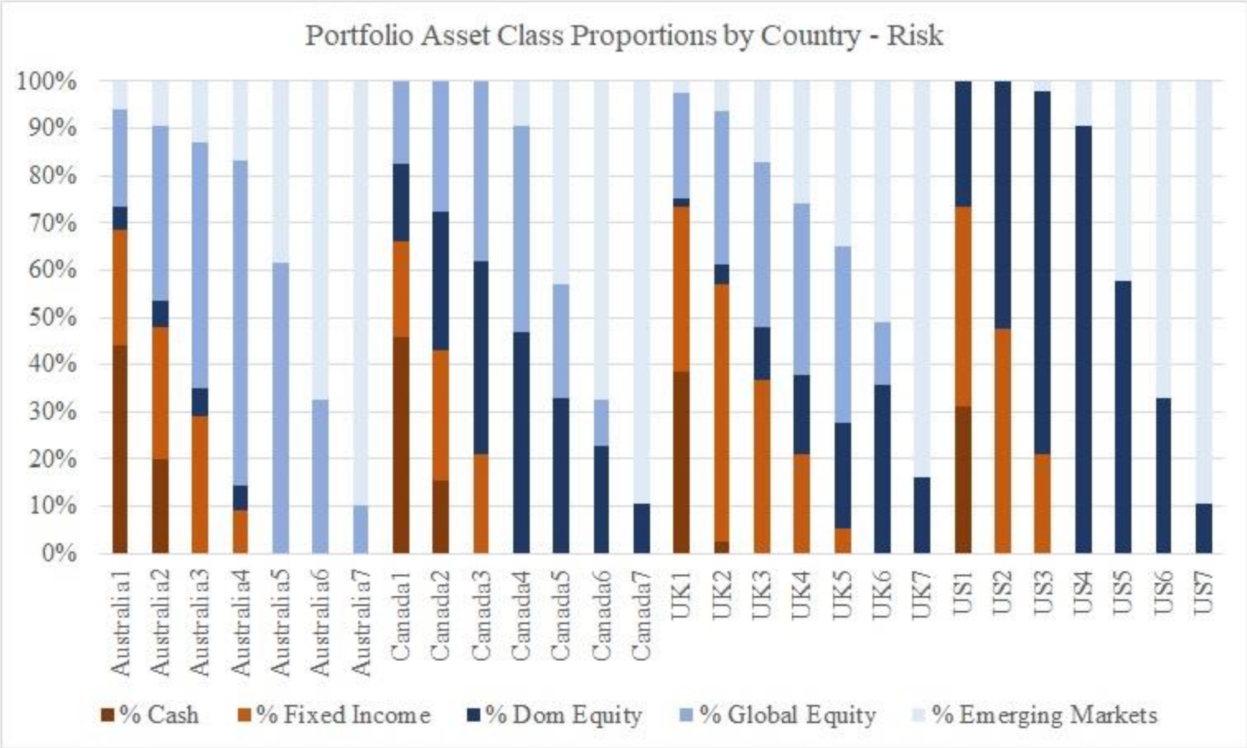
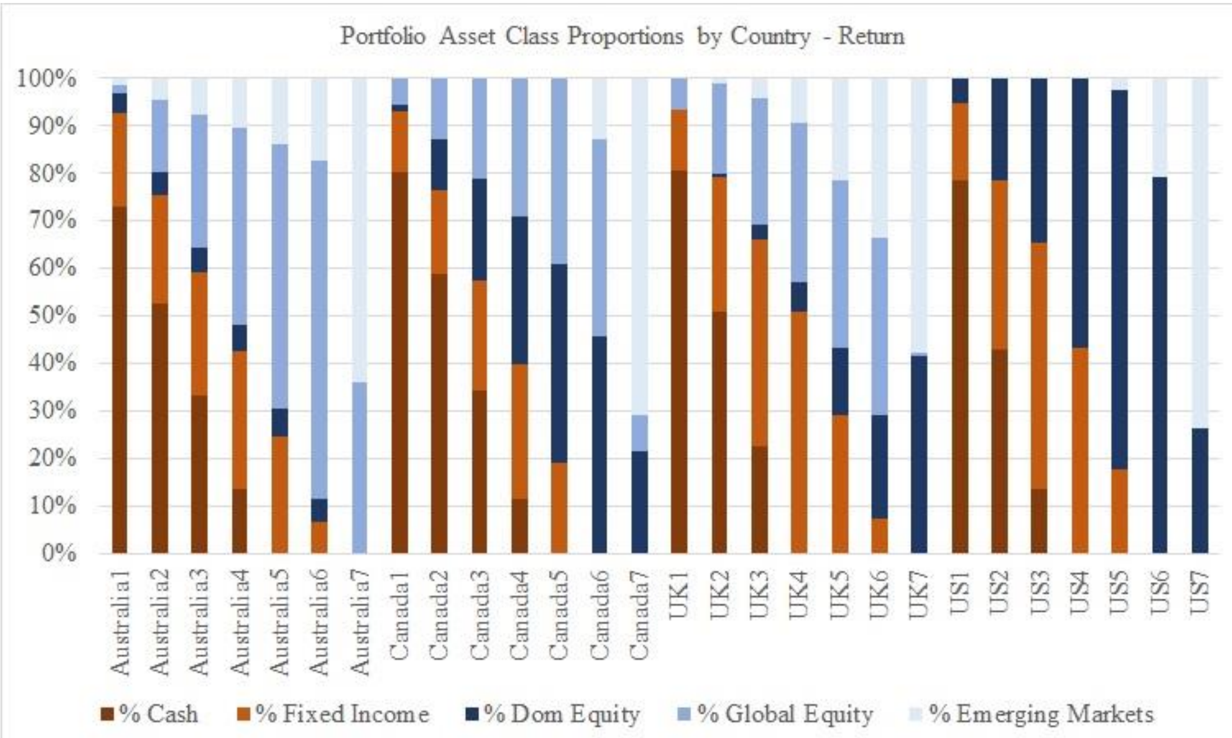


Figure 3. Defensive vs Growth Distributions Based on the Seven Portfolios Distributed by Increments of Risk



When the portfolios were distributed by equal increments of return (Figure 4), we ended up with a more balanced distribution of fixed income and equity positions for the seven portfolios for each country. In Australia and the United Kingdom there were some fixed income assets up to and including portfolio 6 of the seven portfolios and into portfolio 5 for Canada and the United States.

Figure 4. Defensive vs Growth Distributions Based on Even Return Distribution

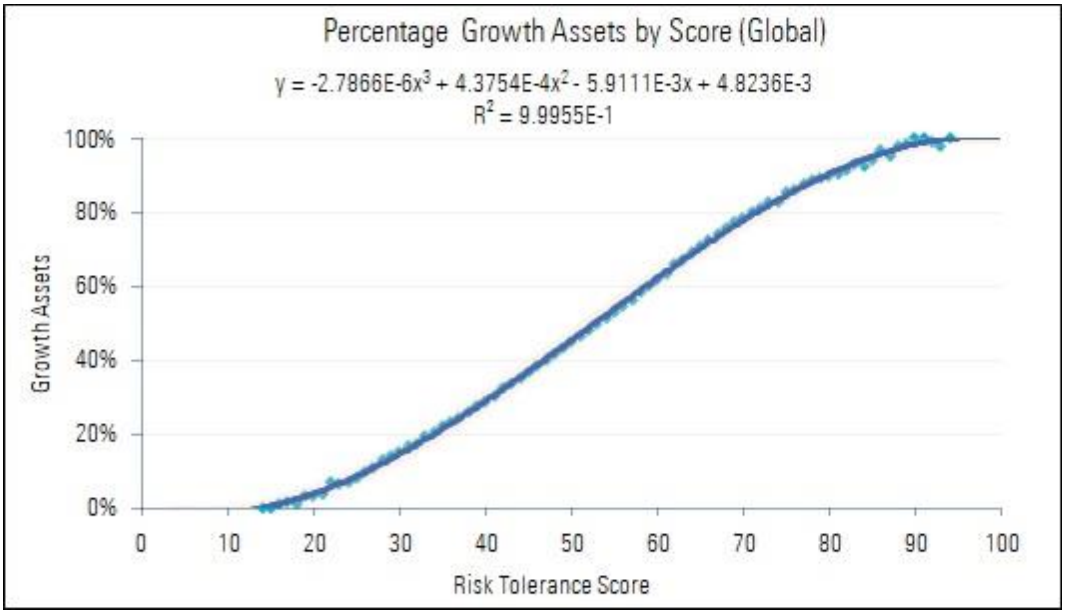


For the balance of the analysis, we compared the seven portfolios constructed by the return distribution to the four methodologies and did not utilize the risk distributed portfolios. The return distributed portfolios more closely reflect actual behaviour in the marketplace and expectations of regulators.

Comparing Expected Equity and the Efficient Portfolios

Davey (2015) used 80,000 responses to the FinaMetrica risk-tolerance assessment. One of the questions asks individuals how much they expect in High Risk, Medium Risk, or Low Risk investments. Davey proposed that high risk was 100% equities (growth assets), low risk was 100% defensive (i.e., cash & bonds), and medium risk was a 50/50 split between equities and defensive assets. Davey then mapped the expected growth assets for each risk score. Figure 5 shows the level of expected equity exposure on the y-axis compared to the risk tolerance of investors.

Figure 5. Consumer Expected Growth Asset Exposure Based on Risk Tolerance[5]



For the analysis, we compared the expected equity assets using Davey's (2015) methodology based on the mid-range of the seven risk-profile bands, to the efficient portfolios that were constructed based on distribution by returns (Figure 1). Note that an updated version of Davey's methodology based on 2022 data is used. Table 2 shows the expected maximum equity exposure and the downside drop in the value of investments at which point an investor was deemed to start to become uncomfortable.

Table 3 illustrates the seven efficient portfolios constructed for each country by the equity exposure. The distribution of the portfolio mappings is very consistent across all countries, matching the Davey (2015) methodology, which was based on expected equity within the portfolio. Not surprisingly, portfolio 6 and portfolio 7 both mapped to risk band seven as they were 93% equity or higher.

Table 2. Ranges of Equity or Decline in Value by Seven Risk Bands

	Expected Equity Exposure or Decline	
Portfolio	**Max Equity**	**Maximum Decline**
1	8%	3%
2	20%	8%
3	35%	16%
4	52%	24%
5	69%	34%
6	83%	45%
7	100%	72%

[5] https://riskprofiling.com/Downloads/Asset_Allocation_Mappings_Guide_v3.pdf

Table 3. Comparison of Expected Equity vs. Efficient Portfolios Equity Mapped to Bands

	Equity of 7 Portfolios				Mapped Risk Band			
Portfolio	Australia	Canada	United Kingdom	U.S.	Australia	Canada	United Kingdom	U.S.
1	7%	7%	7%	5%	1	1	1	1
2	24%	24%	21%	21%	3	3	2	2
3	41%	42%	34%	35%	4	4	3	3
4	57%	60%	49%	57%	5	5	4	5
5	75%	81%	71%	82%	6	6	6	6
6	94%	100%	93%	100%	7	7	7	7
7	100%	100%	100%	100%	7	7	7	7

Comparing Downside Risk Expectation and Efficient Portfolios on Downside Risk

Davey (2015) outlined the expectation for investors to downside risk or largest falls (methodology 2) and concluded that it is largely consistent with expectation of equity exposure. Specifically, Davey noted that, "… predicted performance is the mean minus 3.5 standard deviations for estimated returns" (p. 35).

The use of 3.5 times standard deviation is atypical and reflects a 99.98% certainty or 1 event in 2,149 years if annualized data are assumed. Most VaR analyses use 90%, 95%, or 99% certainty. Keeping in mind that a VaR is only concerned about the downside tail, we used the following multipliers: 1.28, 1.65, and 2.33 times the Standard Deviation for 90%, 95%, and 99%, respectively, to calculate the VaR, depending on the level of certainty desired.

When the seven portfolios for the four countries were mapped to the same seven risk bands a relatively clear distribution emerged. The United Kingdom seems to require additional risk to achieve incremental increases in the return. The downside expectations shown in Table 4 are based on an updated version of Davey's (2015) methodology (i.e., updated with 2022 data).

Table 4. Comparison of Downside Expectation vs Efficient Portfolios at 3.5x SD

		VaR @ 3.5x				Mapping to 7 Risk Bands			
Port	Largest Downside	Aus	Can	U.K.	U.S.	Aus	Can	U.K.	U.S.
1	3.0%	7.8%	6.9%	7.2%	6.5%	2	2	2	2
2	8.0%	11.5%	9.1%	11.0%	10.3%	3	3	3	3
3	16.0%	20.0%	16.5%	19.9%	17.3%	4	4	4	4
4	24.0%	30.3%	24.8%	30.9%	27.5%	5	5	5	5
5	34.0%	41.6%	33.9%	45.9%	40.8%	6	6	7	6
6	45.0%	52.8%	44.7%	64.0%	56.2%	7	6	7	7
7	72.0%	73.4%	68.4%	84.2%	84.3%	7	7	7	7

Applying the MIFiD-II VaR Calculations

The seven model portfolios were analysed based on five-years of monthly data ending in 2022. These data were used to calculate the monthly standard deviation and then annualized. Results are shown in Table 5.

Table 5: Mapping Seven Portfolios Across Four Countries Based on Five-year Standard Deviation and MIFiD-II Methodology

	Australia		Canada		United Kingdom		U.S.	
Portfolio	**SD**	**Risk Class**	**SD**	**Risk Class**	**SD**	**Risk Class**	**SD**	**Risk Class**
1	1.7%	2	1.2%	2	4.2%	3	1.1%	2
2	3.7%	3	3.8%	3	6.4%	4	3.4%	3
3	5.6%	4	6.6%	4	8.6%	4	5.2%	4
4	7.4%	4	9.0%	4	10.3%	5	7.0%	4
5	9.1%	4	11.7%	5	12.2%	5	9.4%	4
6	10.6%	5	13.6%	5	12.7%	5	11.9%	5
7	10.6%	5	13.0%	5	13.4%	5	12.9%	5

Using the MIFiD-II mapping ranges and five years of monthly data shows that all the portfolios are more tightly clustered and would be classed in risk bands 2 to 5. It is important to observe that even the 100% cash portfolio has a standard deviation that would be mapped into risk band 3 or 4 in all counties. With recent interest rate hikes even the five-year cash portfolio would display significant volatility. It is difficult to conceive what products would be considered appropriate for MIFiD-II's first two risk bands. Similarly, even the most aggressive of all equity portfolios are mapped to risk bands 5. It appears as if the regulator considers any well-constructed, diversified portfolio – even when 100% in equity investments – not the highest risk level for two bands of investors.

Notice that for Canada that Portfolio 7's risk is less than Portfolio 6. The portfolios utilized are based on optimized long-term data. In the short five-year period, this can lead to unexpected risk outcomes. We ran the MIFiD-II methodology against five-year data from 2013 to 2017 and found "inverted outcomes" compared to the most recent five years. In the period 2013 to 2017, U.S. markets materially outperformed the rest of the world with U.S. portfolios exhibiting the lowest risk. In the last five years a different pattern has emerged. The conclusion is that using rolling five-year periods will not result in consistent outcomes of risk expectation for investor's portfolios.

We completed the same exercise using the historical long-term indices for these portfolios. Results are shown in Table 6. Although there is a slightly broader distribution of the portfolios across the seven MIFiD-II risk classes, no products, including cash, fall into Risk Class 1 or 2 for standard deviation below 2% per year. There is, however, a more realistic mapping of the 100% equity portfolios (at least to Risk Class 6 from 5).

Table 6: Mapping Seven Portfolios Times Four Countries Based on Long-term Indices and MIFiD-II Thresholds

	Australia		Canada		United Kingdom		U.S.	
Portfolio	SD	Risk Class	SD	Risk Class	SD	Risk Class	SD	Risk Class
1	4.5%	3	3.6%	3	4.0%	3	3.4%	3
2	5.8%	4	4.6%	3	5.5%	4	4.9%	3
3	8.5%	4	7.0%	4	8.4%	4	7.3%	3
4	11.7%	5	9.7%	4	11.9%	5	10.6%	5
5	15.1%	6	12.6%	5	16.6%	6	14.8%	5
6	18.6%	6	16.0%	6	22.1%	6	19.6%	6
7	24.7%	6	23.1%	6	28.3%	6	28.0%	6

RiskCAT Results

The RiskCAT model introduced by Grable (2008) proposed a multiplicative "profiler score" from 0.0 to 2.5 and a mapping into an index of 75% U.S. large cap and 25% U.S. small cap equities. Grable classified this index as a Beta = 1 and then mapped it to a score of 1.0 on the scale. Using this approach, an investor with a profile score of 0.5 would be mapped to an index of 50% equities and 50% cash. An investor with a score of 2.0 would map to 2x the index, which means leverage of 50% (i.e., doubling the level of risk).

In the original model, Grable referenced an "index" with a standard deviation is 23.38% and a VaR of 12.43% after a 10.95% return. We recalculated the index VaR based on this study's indices (Morningstar US Market TR USD and the Russell 2000 Total Return Index - a shorter history than used by Grable) using the same 75%/25% split. Assuming the portfolio is unconstrained by time horizon and risk capacity then the mapping simplifies to a simple risk scale from 0 to 2.5, with seven risk bands as shown in Table 7.

Table 7. VaR Based on RiskCAT

Portfolio	Risk Class	VaR @ 68%	VaR @ 90%	VaR @ 95%	VaR @ 99%
1	0.36	2.1%	4.4%	7.5%	13.2%
2	0.71	7.8%	12.5%	18.7%	30.0%
3	1.07	13.6%	20.6%	29.9%	46.9%
4	1.43	19.3%	28.7%	41.1%	63.8%
5	1.79	25.1%	36.8%	52.2%	80.6%
6	2.14	30.9%	44.9%	63.4%	97.5%
7	2.50	36.6%	53.0%	74.6%	114.4%

Table 8 illustrates what occurs when the seven portfolios for each of the four countries is mapped to the RiskCAT using 7 equal bands.

Table 8. VaR Mapping at 90% Certainty Based on RiskCAT

Portfolio	90%	Australia		Canada		United Kingdom		U.S.	
	VaR	VaR	Risk Class	VaR	Risk Class	VaR	Risk Class	VaR	Risk Class
1	4.4%	2.2%	1	1.1%	1	1.6%	1	1.2%	1
2	12.5%	1.4%	1	1.0%	1	1.1%	1	0.6%	1
3	20.6%	1.2%	1	1.0%	1	1.3%	1	1.1%	1
4	28.7%	4.4%	2	3.3%	1	4.4%	2	3.9%	1
5	36.8%	8.0%	2	5.9%	2	9.1%	2	7.9%	2
6	44.9%	11.6%	2	9.1%	2	14.9%	3	12.7%	3
7	53.0%	18.5%	3	17.1%	3	21.4%	4	22.1%	4

A variation in the certainty level should result in a change in the breakpoints from RiskCAT and in the calculated VaR from the seven portfolios. We considered recalibrating the investment index for each country, although this became more problematic as countries outside the United States are unlikely to have as strong a concentration on their own domestic equities, have as developed a small cap market and definitely not be as concentrated in U.S. equities.

In reviewing the RiskCAT results, one can see that "by design" the system was conceived to support up to 2.5 times the risk and return of a 100% equity portfolio, so portfolio 3 aligns with this 100% equity portfolio. It is worth noting that when RiskCAT was originally published, the model was developed using a group of advisors in a session. At that time, the belief in a "secret sauce" for investing was more dominant than today when most financial advisors are focused on marginal improvements in returns or reductions in risk from relevant indices. As such, we utilized the same methodology and rescaled RiskCAT using a more contemporary assumption of 1.25x market as the upper bound for an investor that has high tolerance for risk, capacity for loss, and time horizon (called RiskCAT 2 here). The result of the rescaling is shown in Tables 9 and 10.

Table 9. Thresholds Based on RiskCAT 2 (Rescaled Beta)

Portfolio	Risk Class	VaR @ 68%	VaR @ 90%	VaR @ 95%	VaR @ 99%
1	0.18	0.8%	0.3%	1.9%	4.7%
2	0.36	2.1%	4.4%	7.5%	13.2%
3	0.54	4.9%	8.4%	13.1%	21.6%
4	0.71	7.8%	12.5%	18.7%	30.0%
5	0.89	10.7%	16.5%	24.3%	38.5%
6	1.07	13.6%	20.6%	29.9%	46.9%
7	1.25	16.5%	24.6%	35.5%	55.3%

Table 10. Mapping Based on RiskCAT 2 (Rescaled Beta)

Portfolio	90%	Australia		Canada		United Kingdom		U.S.	
	VaR	VaR	Risk Class	VaR	Risk Class	VaR	Risk Class	VaR	Risk Class
1	0.3%	2.2%	2	1.1%	2	1.6%	2	1.2%	2
2	4.4%	1.4%	2	1.0%	2	1.1%	2	0.6%	2
3	8.4%	1.2%	2	1.0%	2	1.3%	2	1.1%	2
4	12.5%	4.4%	3	3.3%	2	4.4%	3	3.9%	2
5	16.5%	8.0%	3	5.9%	3	9.1%	4	7.9%	3
6	20.6%	11.6%	4	9.1%	4	14.9%	5	12.7%	5
7	24.6%	18.5%	6	17.1%	6	21.4%	7	22.1%	7

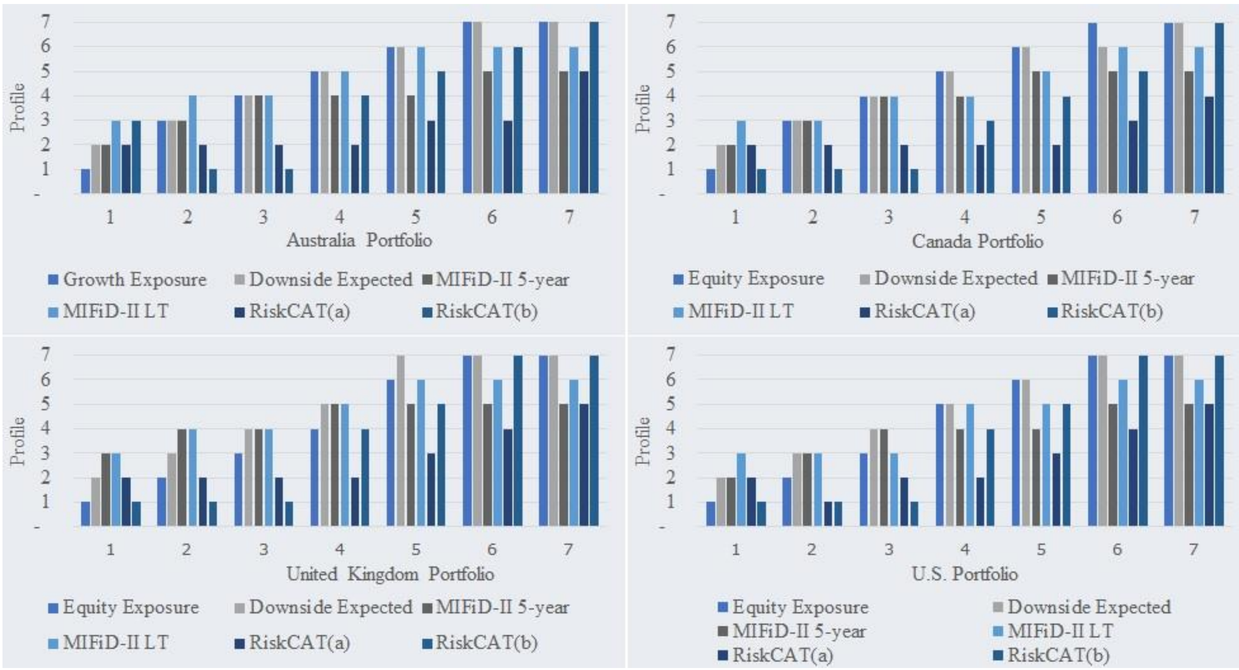
Comparing the Six Methodologies

Figures 6 illustrates for each of the four markets, how each of the six methodologies mapped each portfolio. Using the assumption that the seven portfolios that are evenly distributed by the level of return in the portfolio is an approach for seven bands of risk (not necessarily the case, but a baseline assumption), one can observe:

Many models struggle with what a financial advisor would consider an “ultra conservative” band. The risk of cash in isolation or the most conservative efficient portfolio (which has a lower SD than cash) often falls in risk band 2 or 3.

The Davey (2015) equity exposure methodology (#1) has been used in production with many countries and for several years. Overall, when the Davey approach is compared to a simple linear mapping of the seven portfolios into seven risk bands, it is the closest overall, followed by the RiskCAT 2 methodology. Davey’s downside expectation (#2) (VaR), even though based on an exceptionally high certainty requirement, places third overall.

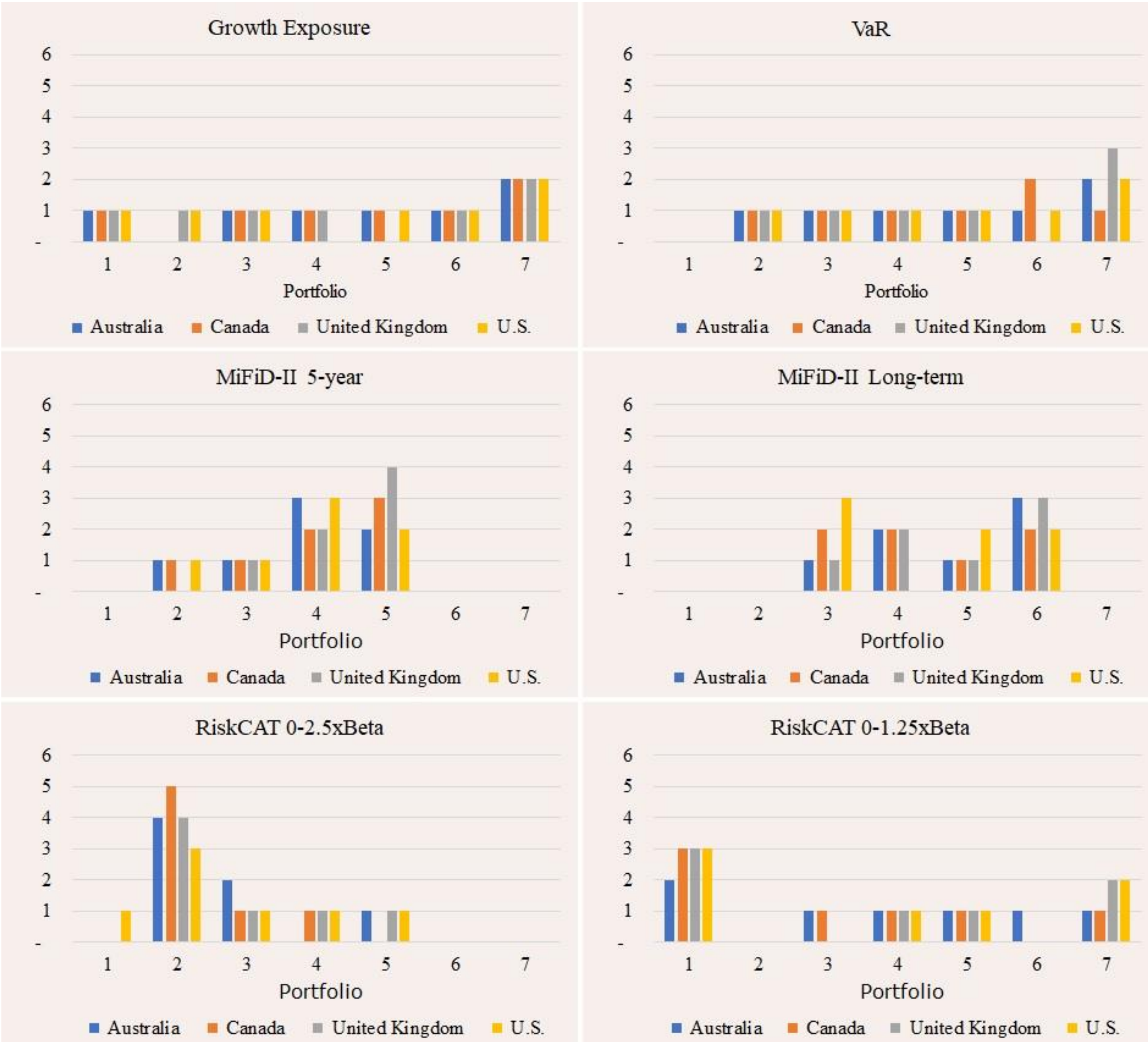
Figure 6. Mapping Seven Portfolios Using Six Methodologies into Seven Risk-bands



The two approaches outlined by Davey based on FinaMetrica data were the most evenly distribution with seven portfolio mapping into seven client risk bands, but from a product perspective the methodology using expected equity exposure can only be utilized at a diversified portfolio level, not at a product level (i.e., every common stock on every stock market is considered the same). Complex solutions involving guarantees or leverage are also outside of the ability to analyse easily.

The MIFiD-II methodology (#3) using five-year data was the most challenged models at the tails, mapping all portfolios into the middle three or four risk bands. Although applying the long-term indices marginally improved the distribution, all portfolios were still clustered in 4 of the 7 risk bands. This methodology appears to be constructed to bucket the universe of all products at extremes of risk on both ends (lower than cash and higher than a 100% equity aggressive portfolio) where the products in isolation might make sense individually for a client unless part of a broader portfolio or investment strategy. This would appear to indicate a “risk profile test” should be scaled to only map into the middle 4 bands.

Figure 7. Six Methodologies Mapping into Seven Risk-bands



The RiskCAT methodology (#4) was the most removed from the consensus for the simple distribution with 3 to 5 portfolios mapped into risk band 2 for all countries. As expected, this was largely caused by the scaling of 2.5x equity markets as the high point of the range. When rescaled to 1.25x market (i.e., a RiskCAT score of 2 was set to a Beta of 1), it was a closer mapping to the seven evenly distributed bands, but still was less adaptive on the tails (risk bands 1 and 7). The challenge appears to be a simple linear mapping is not reflective of the non-linear shape of the risk/return curve where significant increase in return on the conservative end of the spectrum can be achieved with relatively little increase in risk whereas on the risky investing extreme the same increase in return may require exposure to much riskier asset classes.

We also compared the mapping results with a simple mean and standard deviation and a correlation analysis between each of the methodologies (Table 11). It was determined that there was an average standard deviation of +/- 1.1 bands between the methodologies, but it could be as high as 1.5 bands (e.g., the U.S. market). If we remove the MIFiD-II 5Yr and the originally 2.5x scaled RiskCAT, the Equity Exposure, Maximum

Expected Decline (VaR), MIFiD-II Long-term and RiskCAT2 average between 0.95 and 0.97 with the other 3 methodologies and agree on the bands +/- 0.8 risk bands.

Table 11. Correlation Between Mapping Results of Methodologies

Equity Exposure	VaR	MIFiD 5Yr	MIFiD LT	RiskCAT	RiskCAT2		Avg Corr
1.00	0.98	0.84	0.96	0.81	0.92	**Equity Exposure**	0.92
0.98	1.00	0.88	0.96	0.80	0.94	**VaR**	0.93
0.84	0.88	1.00	0.86	0.65	0.78	**MIFiD 5Yr**	0.83
0.96	0.96	0.86	1.00	0.77	0.94	**MIFiD LT**	0.91
0.81	0.80	0.65	0.77	1.00	0.88	**RiskCAT**	0.82
0.92	0.94	0.78	0.94	0.88	1.00	**RiskCAT 2**	0.91

Overall, the results from this study show a strong correlation in the mapping results across all countries. Furthermore, all methodologies "scale up" as the portfolios become riskier.

Conclusions

Although use of equity asset exposure is an interesting heuristic, it may not be appropriate as the best metric for determining risk in non-efficient portfolios. In most countries, there is between a 50% and 100% difference in the standard deviation of primary equity asset classes. Using a metric of total growth assets does not recognize this properly. FinaMetrica historically was very clear to provide illustrative portfolios with comprehensive "risk return guides" for each country. They also stated that their methodology can only be reasonably applied to diversified/well-constructed portfolios.

Additionally, although alignment with downside risk or VaR appears to be the best approach, as outlined in this study, basing it on a simple five- or 10-year standard deviation can vastly understate the risk for an investor when the volatility is low for a period of time. Any mapping methodology that relies on a measure of standard deviation or VaR needs to be properly calibrated for each market. As illustrated in this study, financial advisors are likely to see significant variation in the overall volatility of markets, the efficient reliance on equities to reduce risk, and differences in the risk/return curve and market efficiency in general. It is also worth noting that using a linear mapping is problematic where the risk/return curve is far from linear and significant returns on the low end might be achieved with little incremental risk compared to the increased risk on the high end for smaller returns.

We considered taking the average of all six methodologies as "better consensus mapping" but the traditional RiskCAT variances skewed the results. We might consider this in the future removing this model from the analysis.

Many compliance departments and regulators are looking for simple definitions and easy to explain systems to determine suitability – put a risk rating on every product, rate the risk level suitable to an investor and ensure that everything the investor owns is at or below the approved risk level. Simplistic solutions, although easier to manage, do not reflect that people and products are not the same and product manufacturers can invent investment products that in isolation could be unsuitable for any client, but in combination with other solutions may form a portfolio that is optimal for a client. Simplistic use of a single timeframe, whether short, medium or long term can reflect one aspect of the product or portfolio risk but obscure other aspects. Longer time horizons can make downturns like experienced in 2020 with COVID "disappear", whereas short timeframe can significantly understate risk in quiet periods.

Implications

Evolving compliance solutions is challenging and often only occurs when something is considered "broken" by complaints. None-the-less there are some considerations financial planners should consider to ensure best practices for clients:

There is merit in having a different scale for product risk than people risk so that solutions that in isolation are outside what would be considered suitable bands are differentiated. Implying that every product regardless of risk is suitable for a very high risk-taking investors and only those investors is too simplistic.

Ensure that the mapping methodology utilized is designed to map into the holistic position of the investor. Using the MIFiD-II model as an example, it appears clients should be mapped into the middle four bands – not all seven product risk bands.

Consider multiple timeframes for measuring risk of products, a long-term horizon to capture risk on the same timescale as the financial plan, the short-term risk as usually defined by regulators, and the highest-risk, short-term experience, over the longer history of the product. If the objective is to ensure clients are not taken by surprise, ensure the measure of risk being used is not losing this perspective.

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APPENDIX A

Table 12. Asset Class Risk/Return by Country

Market	Asset Class	Standard Deviation	Arithmetic Average Return
Australia	Cash	5.07%	7.51%
51 years	Fixed Income	7.47%	8.05%
	Australian Equity	23.80%	11.58%
	Global Equity	19.66%	12.33%
	Emerging	30.82%	13.51%
Canada	Cash	4.00%	5.07%
73 years	Fixed Income	8.02%	6.36%
	Canadian Equities	16.53%	11.19%
	International Equities	16.50%	11.14%
	Emerging Markets	27.76%	13.11%
United Kingdom	Cash	4.52%	6.06%
66 years	Fixed Income	10.25%	8.48%
	United Kingdom Equity	27.05%	13.93%
	Global Equity	18.75%	12.36%
	Emerging Markets	32.97%	15.51%
U.S.	Cash	3.82%	4.87%
44 years	Fixed Income	7.10%	6.65%
	U.S. Equity	17.63%	11.92%
	U.S. Small Cap Equity	18.97%	12.50%
	International Equity	21.50%	11.25%
	Emerging Markets	33.11%	14.48%