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Abstract

We compare the investment philosophy and management style of the Norwegian Government Pension Fund Global (GPF), Canada Pension Plan (CPP), and Australian Future Fund (FF) with focus on extracting the role of alternative assets in these portfolios. We decompose fund returns into manager skill (alpha) and exposure to (1) the market, and other compensated factors, or (2) benchmark indices. We find that GPF and FF's returns are consistent with their stated models. FF's results indicate that if deployed effectively, exposure to alternative assets can improve risk-adjusted performance. However, as we observe for CPP, the illiquid and opaque nature of alternative assets can also provide scope for manager-smoothed returns, especially in combination with internal investment management. Overall, our paper proposes that the inclusion of alternative assets in a long-term institutional portfolio can provide diversification benefits, but we caution that accurate and timely disclosure of investment performance is critical. The performance of alternative assets should be assessed with a healthy degree of scepticism in cases where management and reporting of the assets is performed by the same group.

Introduction

Norway, Australia and Canada all have sovereign wealth or pension funds with investment models that have been widely praised in the investment community, though each uses a different approach to investing for future generations. The strategies employed in these funds can differ in many respects – internal versus external management of investments, active versus passive management, approach to asset allocation – and each model has its strengths and weaknesses. Additionally, since the global financial crisis of 2007-2009, public markets have offered lower returns, leading to increased focus on alternative asset for proposed diversification and returns benefits. Therefore, we seek to understand the role of alternative assets in a long-term institutional portfolio's risk-adjusted performance and the impact of investment management style on their reported performance. We focus on one major fund representing each country, using Norway's Government Pension Fund – Global, the Canada Pension Plan, and Australia's Future Fund (hereafter GPFG, CPP and FF, respectively). To our knowledge, this study is the first with a specific focus on the role of alternative assets in these three models and comparing how investing in alternatives affects risk-adjusted performance.

We find that FF and GPFG returns can be well-explained by exposure to relevant benchmarks and are consistent with their investment models. Removing alternative assets from GPFG's portfolio does not markedly change their performance, which is unsurprising given their limited focus on this asset class. We find that FF's positive and significant alpha disappears when alternative assets are removed from their investment universe, and thus believe that exposure to alternative assets can improve risk-adjusted performance if deployed effectively. However, we caution that the illiquid and opaque nature of alternative assets provides scope for manager-smoothed returns in the case of internal investment management, as seen in CPP results after they moved to an active investment style in 2006. We attribute this partially to the internal versus external management style of CPP and FF respectively. Thus, we believe that the inclusion of alternative assets in a long-term institutional portfolio can provide diversification benefits but given what we observe for CPP, should be approached with a healthy degree of scepticism in cases where management and reporting of the assets is performed by the same group.

Literature Review

To understand the three models, we review available literature on the Norway, Canada and Australia models with focus on asset allocations and investment style of the funds. Using GPF, FF and CPP as representative of these models, we explore the background and context for each fund, how each model is employed, and how performance of each fund is benchmarked.

2.1 Pension fund vs. sovereign wealth fund

Of the funds selected, two are sovereign wealth funds (GPF and FF), while one is a pension fund (CPP). Both sovereign wealth funds (SWFs, hereafter) and pension funds are institutional investors with long-term horizons (Boubakri, Cosset, & Grira, 2016). Although many definitions of SWFs can be found, most researchers agree that SWFs are owned by the government and invest domestically or internationally to seek commercial profits (Fotak, Gao & Megginson, 2017). Sovereign wealth funds serve to achieve national objectives, whereas pension funds are set up as long-term vehicles to finance public pensions and other related benefits (Blundell-Wignall, Hu, & Yermo, 2008).

Government ownership means that SWFs may deviate from principles relating to wealth maximization as they may be subject to political influence (Fotak, Gao & Megginson, 2017). In reading relevant research, we find no indications that researchers believed either SWF of focus (the GPF and FF) acted in a sub-optimal manner to achieve political objectives (Megginson & Fotak, 2015; Rozanov, 2015; Rozanov, 2017; Towner, 2014; Xu, 2017). Investments are governed by independent boards for each fund, and thus we can reasonably treat investment decisions made by GPF and FF to be in pursuit of traditional investment objectives and not political objectives (Towner, 2014; Australian Government, 2017). The aim of this paper is to investigate the relationship between asset classes and portfolio returns, and thus GPF, CPP and FF are comparable as all three seek the best returns for a given asset class and risk allocation with a long-term horizon.

2.2 Norway's GPF

History and background

In 1990 the Norwegian Parliament passed legislation to create the GPF. A portion of petroleum revenues received by the government would be transferred to the fund to “support the government’s long-term management of petroleum revenue”

(NBIM, 2018b). The aim is to invest petroleum wealth and gradually phase it into the economy. In particular, GPFG's mandate emphasises the importance of long-term savings and facilitating intergenerational wealth transfer (Rozanov, 2017).

To help achieve GPFG's long-term goals, the government is limited to withdrawing 3 percent of the fund's value in a year, which is linked to the real expected return of the fund (NBIM, 2018a). The limit of withdrawal was lowered from 4 percent in 2017 to reflect updated expectations of the portfolio's return. This means the GPFG's inflows of assets are from the transfer of the government's share of petroleum revenues and returns generated by GPFG, while liabilities are the government's withdrawals from the fund. The transfers from the government can be more volatile, as they are driven by petroleum wealth and therefore commodity prices, but by keeping the withdrawal rate to less than the expected real return, the Norwegian government prevents erosion of capital in the fund, and thus ensures that the GPFG will be invested in perpetuity.

One interesting point to note is that although the GPFG, the Government Pension Fund - Global has 'pension' in their name, the liabilities of the fund are not pension liabilities. Rather, the liabilities result from the ability of the government to withdraw 3 percent of the fund for government spending. As noted in Rozanov (2017), as the size of the fund was growing, some members of Norwegian society wished to reconsider the limit on withdrawals, allowing for higher government spending. To sway public opinion, officials in charge of the fund changed the name of the fund from 'petroleum fund' to 'pension fund', believing it would be harder to increase public spending from the fund if the assets were perceived to be pension money instead of oil money. The name change did not affect the operations of the fund, and the GPFG is in effect a perpetual endowment fund.

The fund received its first transfer from the Ministry of Finance in 1996 and was initially invested entirely in bonds outside of Norway. The investment model was first changed in 1998, when 40 percent of GPFG's investments were allocated to equities. The government, working with expert advisors, have continued to adjust the laws surrounding the management of the GPFG, giving rise to the current model, colloquially called 'the Norway model' of investing.

The Norway model

The Norway model is characterised by a focus on public securities and liquid markets, a belief in market efficiency, attention to beta-driven returns (as opposed

to alpha returns), and a preference for internal management of assets (Chambers, Dimson & Ilmanen, 2012; Rozanov, 2017). A focus on beta returns has an inherent assumption that the market is efficient, returns are driven by exposure to systematic risk, and it is difficult to outperform the market consistently. This belief gives rise to a unique aspect of the Norway model: a focus on liquid securities. The investment policy of the fund is guided by strategy established from the nation's legislature and set by an independent board of experts, preventing political pressures from influencing the fund's managers (Towner, 2014; Megginson & Fotak, 2015).

As of 2018, the fund is allowed to allocate 62.5 percent into equities, with the remainder of the fund in fixed income, and the portfolio must be rebalanced if the equity allocation deviates by more than 4 percent from its target allocation (Ministry of Finance, 2017). The fund is also permitted to invest up to 7 percent of capital in unlisted real estate. The policy portfolio has changed substantially from the fund inception when the fund was invested only in government bonds (NBIM, 2018b). Shortly thereafter, 40 percent of the fund was allocated to public equities, with the portion of the bond portfolio being converted to equity holdings by Norges Bank Investment Management (NBIM), the manager of the GPF, in the first half of 1998. Though 62.5 percent of the fund is allocated to equities, GPF is restricted from holding over 10 percent of the shares in any single firm, restricting the opportunity to take a controlling interest in a portfolio company.

The scope for deviation from the benchmark has varied over time and is currently limited to a small tracking error of 125 basis points (NBIM, 2017c). As noted in Chambers et al. (2012), a small tracking error constrains the amount of active management that can be undertaken in managing the fund, but the model should function well if modern investment theory captures the realities of investing (Ambachtsheer, 2016). Chambers et al. (2012) note that given the fund's very long horizon and large capital inflows, combined with its minimal short-term obligations, it is very well-positioned to tolerate high levels of illiquidity in its investments. This makes illiquid investments such as real estate, infrastructure, private equity, or other alternative assets well-suited investments for the fund. Despite being in the position to tolerate illiquidity, Rozanov (2017) believes that GPF lags behind its peers in failing to hold and earn a liquidity premium from illiquid assets, instead effectively paying for liquidity that is not needed by the fund.

In addition to tracking error, GPF also manages risk using concentration analysis, factor exposure and liquidity risk (NBIM, 2017c). In concentration

analysis, GPFM investigates which investments do not overlap with the benchmark index and determines the concentration of this portfolio. Concentration is measured for individual companies, industry sectors and geographic regions. More concentrated portfolios will often have a higher level of risk than diversified portfolios, so GPFM aims to balance concentration and diversification. Factor exposure entails measuring exposure to systematic factors which may offer higher reward but have exposure to higher risk, such as small-cap companies, value companies, and emerging markets. Finally, liquidity risk focuses on the fund's ability to quickly change the fund's composition. Chambers et al. (2012) suggested that with the addition of real estate to the portfolio, the four risk measures GPFM currently employs have become inadequate, suggesting additional measures of risk that focus on absolute return and absolute risk are required.

The Norway model is also characterised by managing most of the portfolio in-house – currently there are 550 employees managing the fund (NBIM, 2017a). As noted in Megginson & Fotak (2015), the index-matching strategy used by GPFM allows the fund to manage over 95 percent of its investment portfolio internally. A preference for internal management mitigates principal-agent problems and allows for cost control and economies of scale (Rozanov, 2017).

Benchmark portfolio

The fund's performance is measured against internal operational reference portfolios for equities and bonds (the benchmark), with the reference portfolio for equities constructed by FTSE Group and the reference portfolio for fixed income constructed by Bloomberg L.P. (NBIM, 2017b). The reference portfolios include securities that represent a “neutral and appropriate strategy”. However, because the reference portfolios do not include investments in unlisted real estate, any investment into this asset class contributes to tracking error.

The benchmark portfolio used by GPFM has developed over time, beginning with a very conservative fixed income portfolio in 1998, in line with the conservative investment strategy followed by the fund when operations began (Rozanov, 2017). The evolution of the benchmark has continued, adding some emerging markets to the equities benchmark in 2000, corporate and securitised bonds in 2002, small-cap companies to the equities benchmark in 2007, and finally the remaining emerging markets in 2008.

2.3 Canada's CPP

History and background

In 1965 Canada's government passed laws to create the CPP with the aim of establishing a system to fund old-age, disability and disability insurance. Contributions from Canadian citizens were invested into a portfolio of domestic bonds, and this was not changed until 1996 when an actuarial report determined that without changes, the CPP would be out of funds in 20 years (Sarney & Preneta, 2001). The government of Canada reformed the CPP by raising contribution rates, reducing benefits, and creating the Canada Pension Plan Investment Board (CPPIB) to manage and invest CPP's assets (World Bank, 2017). The CPP receives compulsory contributions amounting to 9.9 percent of individual Canadians' income, with payments divided equally between the employee and their employer (Government of Canada, 2016). These contributions are used to fund retirement pensions, disability benefits and death benefits to eligible Canadians. Beginning in 2019, the CPP will be enhanced, increasing both contributions from and benefits to Canadians (Government of Canada, 2017).

CPPIB is independent of the elected government in Canada, and is mandated to manage the CPP so that the funds help provide Canadians with financial security in their retirement while ensuring the sustainability of the CPP. This means the CPPIB invests with a very long time-frame and aims to maximise returns without undue risk of loss (CPPIB, 2018d). It also means that the fund should have a perpetual horizon, and returns (or contributions) must be high enough such that pension withdrawals from the fund do not erode the real value of the CPP's assets.

When CPPIB was formed in 1996, funds were initially restricted to passive investments in domestic equities, but this restriction was lifted quickly and CPPIB made its first investment in private equity in 2001, and its first investment in real estate and infrastructure shortly thereafter in 2003 (World Bank, 2017). In 2006, CPPIB made the decision to focus on active management across all asset classes, with the aim of utilising its large asset size, stable liability profile and very long investment horizon to achieve higher returns (Rozanov, 2017). This has given rise to 'the Canada model', as it is known today.

The Canada model

The Canada model of pension investing is characterised by direct investment by internal teams in less liquid private markets, and leadership innovation (Rozanov, 2015). Unlike the Norway model, which limits active ownership, the Canada model specifically focuses on active management to drive returns (CPPIB, 2018b). However, like the Norway model, the Canada model manages most of its portfolio internally, with some benefits from scale.

CPPIB uses a ‘total portfolio approach’, which focuses less on target weights among asset classes and allows the portfolio to be managed as a whole (CPPIB, 2018a). As a result, risks are measured in terms of how each investment contributes to the risk of the portfolio, and focus is placed on maintaining targeted levels of risk-return exposure. Ang, Brandt & Denison (2014) noted that the opportunity cost model is particularly well-suited for long-term investors, as it avoids rigidly set asset allocations and the manager need not maintain positions in asset classes which are very expensive or very cheap. However, though the model is conceptually simple, it can be operationally difficult, as success is contingent on fund managers having the expertise to source, evaluate, and monitor investments beyond information readily available in public markets, as well as make accurate judgements of portfolio trade-offs when reallocating funds. A fund manager must be highly skilled and have access adequate information, both of which raise costs associated with the Canada model. To retain top managers, CPPIB sees a need for competitive compensation and the chiefs of CPPIB are some of the highest paid executives in the retirement fund sector globally (Thompson, 2017), which has drawn criticism in recent years (Marriage, 2015).

Canada’s model splits investment assets into one of four areas: private investments, public market investments, real assets, and investment partnerships (CPPIB, 2018e). In public (listed) market investments, CPPIB focuses on both alpha and beta returns, allowing for returns from both systematic risk and active management. Also notable is CPPIB’s use of both long and short positions in its public market investments. The three other investment areas are non-listed assets, and CPPIB must add value from exploiting inefficiencies in private markets, often becoming a significant enough shareholder to exert meaningful governance over its investments. As noted in Rozanov (2015), the combination of a belief in the ability to add value in illiquid assets and the large scale from managing these investments internally is a feature particular to the Canada model. Furthermore, CPPIB’s focus

on illiquid and private assets allows the fund to take advantage of its long-term investment horizon.

Benchmark portfolio

In managing its portfolio, CPPIB constructs key framework elements dubbed the ‘reference portfolio’, ‘target portfolio’, and ‘strategic portfolio’ to guide investment choices (CPPIB, 2018c). The reference portfolio represents a simple, passive portfolio of publicly-traded securities that could be readily implemented. The weights of equity and bonds in the reference portfolio are set to target a risk level decided by the Board and Management of CPPIB. Additionally, the reference portfolio is expected to achieve at least the long-term rate of return that will sustain the CPP. This rate of return looks at the next 75 years and is re-calculated every three years by the Chief Actuary of Canada. Currently, the risk target in the reference portfolio is the equivalent of a portfolio with 85 percent investment in global equity and 15 percent in Canadian government bonds, which is expected to exceed the 3.9 percent real return needed to sustain the CPP.

The strategic portfolio and target portfolios are guided by the reference portfolio but focus on shorter time frames. Both the strategic and target portfolios, like the reference portfolio, are constructed by CPPIB. The strategic portfolio reflects portfolio diversification using weights across asset classes and geographic regions for the next five years and beyond, while assuming the same risk as the reference portfolio. The target portfolio defines the target weights in asset classes and geographic composition of the investment portfolio for the current year. The target portfolio is reviewed each year, while the reference and strategic portfolios are reviewed every three years.

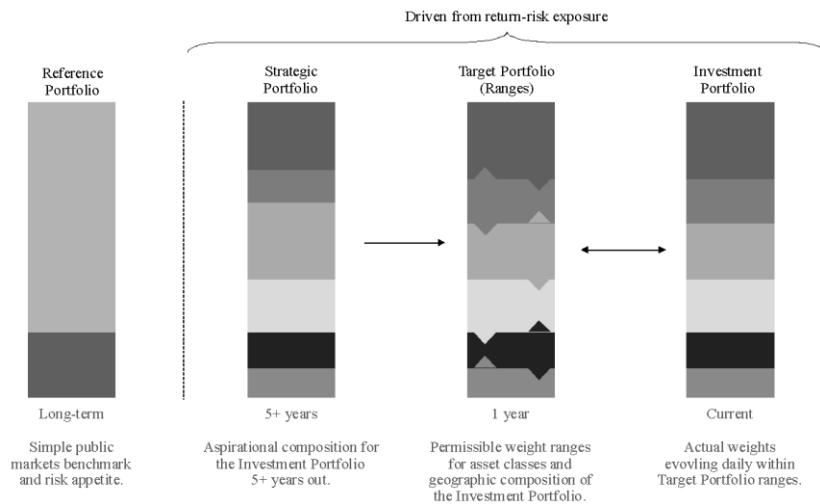


Figure 2.3.1: CPPIB Opportunity cost model elements. Adapted from CPPIB (2017c)

In effect, the CPPIB has two benchmarks which it must measure up against, the reference portfolio and the strategic portfolio. Over the long-term, the fund is expected to create value-added returns in excess of the reference portfolio, while the strategic portfolio is designed to have the same risk as the reference portfolio, but achieve better returns (CPPIB, 2018c). Currently, the strategic portfolio looks at four geographic regions and six asset classes, yielding 24 distinct region-focused asset classes that could be invested to match the returns and risk set by the reference portfolio. These 24 geography-asset class allocations describe the ‘ideal’ portfolio composition over the next five years (Rozanov, 2017). Though one could extract asset allocations for each geography-asset class combination in the strategic portfolio, there are no restrictions or limitations placed on investment allocation from the strategic portfolio, only the risk/return contribution to the portfolio is considered when making investment decisions.

2.4 Australia’s FF

History and background

Australia’s Future Fund (FF) was created by the Future Fund Act in 2006, with the aim of strengthening the country’s financial position while providing for underfunded superannuation (pension) liabilities in the context of an aging population (Australian Government, 2006). Though established to help pre-fund future government pension liabilities, FF is not a superannuation fund, but rather an intergenerational SWF (FF, 2018a; Rozanov, 2017). The distinction is important because the fund is not required to pay any superannuation liabilities and there are no members who make payments into the fund or take money out (FF, 2018a). Additionally, it also means that FF’s management has a fiduciary duty not to current and future pensioners, but rather to the taxpayers of Australia (Rozanov, 2017).

The Australian government transferred starting capital to the FF in lump sums in 2006-2008, which were sourced from budget surpluses and government equity holdings in Telstra, a public owned telecommunication company (Xu, 2017). Since 2008 no transfers to the fund have been made, nor are any planned. The government is prevented from making any withdrawals from the fund before the year 2020, when the fund was expected to help cover underfunded superannuation liabilities (FF, 2018a). However, in 2017 the government announced that it did not plan on making any withdrawals from the fund before 2026. It is also worth pointing out that of the three funds investigated in this paper,

only the FF had a period of time after commencing operations where no liquidity would be required, as the government was prohibited from making withdrawals.

Currently, FF is to provide an average return of 4-5 percent in excess of the Australian consumer price index with an acceptable, but not excessive, level of risk (Australian Government, 2017). Additionally, the fund is required to make investment decisions while minimising impact on Australian financial markets and avoiding any reputational damage to the Australian government. The fund is managed by a board which is independent of the government of Australia, meaning that FF is governed by wealth creation objectives consistent with GPF and CPP.

The Australia model

The Australia model (applying the Yale model) focuses on illiquid securities and private markets, seeking the generation of alpha-driven returns (Rozanov, 2015). At the core of its investment policy, FF believes that markets can be inefficient and therefore skilful management of the portfolio can increase returns (FF, 2018b). This directly contradicts the belief implicit in the Norway model that markets are efficient, and leads to higher investment in alternative assets. As at March 31, 2018 over 40 percent of the FF portfolio was invested in alternative assets (FF, 2018c).

The focus of FF's investments in private markets is the trade-off between liquidity and return, while allowing the fund to take advantage of its long investment horizon (Hudson, 2015). As stated by FF in a position paper (2013), their largest comparative advantages come from being a long-term investor. The fund's long investment horizon allows for higher levels of risk, the inclusion of illiquid assets, and the ability to be counter-cyclical and opportunistic in investment timing. Additionally, the model utilised by FF leans strongly on the benefits of diversification. By reducing risk through diversification, the FF attempts to limit exposure to any single asset class rather than attempting to time markets.

In stark contrast to the internal management preference of both the GPF and CPP, FF's application of the Yale model means that much of the portfolio is managed externally (Hudson, 2015). Under the Yale model, there is a strong preference for using external managers for almost all investments, unless they are routine or indexed. A focus on external management of investments means that the management team at FF is kept deliberately small, limited to around 40 people (Xu, 2017). While GPF and CPP funds are managed in-house to help save costs and align incentives, the management team at FF must create investment strategies and

work with institutional managers. External management comes at a cost, and not just in the form of fees. Using external managers leads to a need for focus on the incentives facing these external managers, and this must be balanced against management of costs to allow for the maximisation of returns (FF, 2018b). In effect, the team at FF must decide incentives, manage expectations, ensure commitment, and monitor performance of investment managers (Xu, 2017). Similar to GPF, FF has a very high degree of financial transparency (Megginson & Fotak, 2015).

Rozanov (2017) highlights two challenges to the implementation of the Yale model to large-scale institutional portfolios like Australia's FF. Firstly, the model is contingent on finding high-quality external managers to access funds. These managers have limited capacity and thus allocation size of funds may be an issue as the fund grows. Secondly, the high-quality managers needed in this investment model tend to be very expensive when considering management and incentive fees.

Benchmark portfolio

As aforementioned, the benchmark return is currently set to an average return of 4 to 5 percent (previously 4.5 to 5.5 percent) above the Australian consumer price index, and this target is set by the government of Australia (Australian Government, 2017). However, in targeting this level of return, the Investment Mandate set by the government states that the fund is limited to taking an "acceptable but not excessive level of risk for the fund". In its Statement of Investment Policies, FF management notes that the return is set in an absolute sense, and is not relative to any peer group or benchmark portfolio (FF, 2018d). Tying the FF objective to a target return rather than a target risk/return trade-off implies that, depending on the level of market risk/return trade-off, FF could be taking on a relatively high level of risk.

As pointed out by Rozanov (2017), a key characteristic of the Yale model is a focus on achieving absolute returns unconstrained by a benchmark. That is indeed the case for FF, who state in their 2016-2017 Annual Report that the fund does not have a fixed strategic asset allocation requiring certain allocations to each investment sector (FF, 2017). The Yale model also prefers to allocate asset risk dynamically using a target asset allocation which is reviewed and updated periodically (Rozanov, 2017). Again, this is the case for FF, which employs a tactical asset allocation on broad groupings of equities, tangible assets, debt, alternatives, and portfolio overlays (FF, 2018d). Details of the tactical allocation were not available, with the FF preferring to be more discreet and publish only

actual portfolio asset allocations in portfolio updates and annual reports. As remarked by Xu (2017), the amount of capital FF deploys necessitates discretion. If investment decisions were known in advance, prices could increase in reaction to purchases or decrease in reaction to divestments, working against the principles of value creation.

2.5 The increasing attractiveness of alternative assets

The growing importance of alternative assets has been noted in the literature and provides a compelling reason to focus on the role of alternative assets in the portfolios of GPF, CPP and FF. Set against the backdrop of today's protracted low-return financial environment, asset allocations of many SWFs have seen a substantially increased share in equities and a steadily decreasing share in fixed income since 2009 (Bodie & Brière, 2013). Terhaar, Staub & Singer (2003) note that alternative assets will play a greater role in portfolios with longer-term horizons, and Cumming, Haß & Schweizer (2014) find that for institutional investors with sufficient time horizons and capital, alternative investments are important for strategic asset allocation. As many SWFs take a more active approach to investing, illiquid investments have become an attractive instrument in the search of long-term returns (Martinez-Oviedo & Redda, 2017). McCahery & de Roode (2017) believe that low interest rates have contributed to increased interest in real estate assets, and found that the strategic asset allocation of SWFs is tilted towards alternative assets, with an average allocation of 22 percent.

Prequin (2018) has found with some consistency that SWFs have increased allocations to private equity since the financial crisis of 2008, while Croce, Stewart & Yermo (2011) found that investment in infrastructure can offer additional diversification to reduce portfolio volatility. Investments in infrastructure can be subject to long lock-up periods, which a long-term investor may be able to tolerate, but can also have hidden risks (McCahery & de Roode, 2017). Timber and farmland is recognised for its inflation-hedging property, but its ability to improve risk-adjusted return has more conflicting findings (Martinez-Oviedo & Redda, 2017).

Considering the smaller market capitalisation of alternative assets relative to public equity and debt markets, the large exposure of SWFs to alternative assets may lead to severe market frictions (McCahery & de Roode, 2017). It can also lead to a conflict between the investment objects of the funds and their investment

policies. Additionally, alternative asset managers charge higher fees, averaging 2 percent management and 20 percent performance fee (Bird, Liem & Thorp, 2013).

Allocating funds to alternative assets with a focus on GPFG, CPP and FF is less well-documented. However, Papaioannou and Rentsendorj (2015) noted the GPFG's increasing risk appetite, later echoed by Bortolotti (Ballard, 2017), who also pointed out that applying the Black-Litterman model could see the GPFG invest 5 percent of the total portfolio in private equity. While the GPFG is currently constrained to real estate, the more alpha-focused FF and CPPIB see alternative assets (including private equity) as part of their mainstream asset allocation strategies. Respectively, FF and CPPIB invest 41.2 percent and 46.3 percent of their total portfolios in alternative assets as of December 31, 2017. Including alternative assets in the portfolios of GPFG, CPP and FF are compelling for three main reasons:

1. **Horizon Matching**, given the long-term income return characteristics offered by some alternative assets and the long-term investment horizon of the funds. For example, the CPPIB holds infrastructure assets for over 20 years and core real estate assets for over 15 years (Liu et al., 2017).
2. **Increasing product variety** in the alternatives space, allowing more precise matching of alternative asset selection to risk appetites and investment objectives. The USD 5 billion Blackstone fund with 20-year lifespan (dubbed its 'core private equity' fund) would seek to invest in slower-growth and safer companies, use less debt in buyouts and charge lower fees (Roumeliotis, 2014; Liu et al., 2017).
3. **Improved return characteristics** overall from higher return per unit of risk.
4. **Diversification** of the existing portfolio from the inclusion of assets that may be uncorrelated with the existing portfolio (Bird et al., 2013). Liu et al. (2017) argues that the private equity asset class is less impacted by extreme market volatility and shows that its alpha (compared to secondary markets) is most prominent when economic conditions are tough.

To our knowledge, this study is the first with a specific focus on the role of alternative assets in the Norway, Canada and Australia models and comparing how investing in alternatives affects the performance of GPFG, CPP and FF.

Models and Theory

In exploring how the addition of alternative asset classes have influenced the funds' performance, our analysis is underpinned by the theoretical frameworks of classic portfolio allocation models and driven by the models of asset pricing.

3.1 Portfolio asset allocation models

Markowitz model

The cornerstone of modern portfolio theory is marked by the Markowitz portfolio theory, whereby through diversification of assets, a more efficient portfolio (as measured by the risk-return trade-off) can be obtained (Markowitz, 1952). Implicitly, such portfolio theory assumes there are two forms of risk: systematic and unsystematic risk, where all investments carry some form of (unavoidable) systematic risk whilst unsystematic risk can be diversified away. Therefore, any measurement of investment performance must necessarily correct for systematic risk (Marlowe, 2014).

The Markowitz model is used extensively by institutional investors to determine asset allocations using mean-variance trade-offs. Papaioannou and Rentsendorj (2015) demonstrate that the GPF's strategic (long-term) asset allocation is broadly consistent with weights generated by the one-period Markowitz model, and propose that GPF's methodology be replicated for other SWFs to ascertain whether there is more widespread conformity of SWFs' asset allocations with those proposed by the Markowitz model.

Sharpe and Tint model

Closely related to the mean-variance asset-only model is the Sharpe and Tint model, which accounts for the coexistence and co-movement of assets and liabilities, a notion particularly applicable to CPP (pension fund) and GPF (pre-determined contribution to state budget that cannot be changed rapidly), but less so to FF given their lack of withdrawals until 2026 (FF, 2018a). Sharpe and Tint (1990) propose that their procedure permits more exact measurement of the relationship between expected returns, risks and hedging characteristics for creating optimally-tailored pension funds.

Black-Litterman model

A challenge faced by both the Markowitz and Sharpe and Tint models is that of input sensitivity, requiring pre-specified levels of expected return. To overcome this and to assist in overcoming the problem of estimation error-maximisation (Lee, 2000), the Black-Litterman model (1992) is seen as a more practical model, using ‘equilibrium’ returns as a neutral starting point (Satchell, 2011). The model generates stable, mean-variance efficient portfolios whilst quantifying investors’ unique insights (otherwise known as ‘views’) in asset allocation (Bodie, Kane & Marcus, 2014), and allowing for constraints or different risk tolerance level from the world average (He & Litterman, 1999). Such characteristics allow the model to be more accessible to institutional investors such as the FF and CPPIB, which aim to optimise on the risk-return profile of the global portfolio.

3.2 Models for asset pricing

Capital Asset Pricing Model

The Capital Asset Pricing Model, hereafter referred to as the ‘CAPM’, yields precise predictions regarding the equilibrium expected return on risky assets (Bodie et al., 2014). The CAPM was first published in 1964 by William Sharpe and in 1965 by John Lintner, who cited the pivotal influence of Markowitz’s 1952 normative model for portfolio selection (see [Section 3.1](#)). As an extension of portfolio theory, the model re-asserts the need to only compensate for exposure to systematic risk and proposes a linear relationship between returns and systematic risk. The latter was supported in early empirical tests conducted by Black, Jensen and Scholes (1972). The CAPM can be expressed as:

$$R_{i,t} - r_{f,t} = \alpha_i + \beta_i \cdot (R_{m,t} - r_{f,t}) + \varepsilon_{i,t} \quad (\text{Equation 3.2.1})$$

where $R_{i,t} - r_{f,t}$ is fund i ’s return in excess of the risk-free rate at time t , $R_{m,t} - r_{f,t}$ is the excess market return and $\varepsilon_{i,t}$ is the random-error term that accounts for returns variation that cannot be explained by exposure to and covariance with the market (β_i).

Carhart 4-Factor model

Nonetheless, there were observations of patterns in average stock returns that could not be explained by the CAPM, such as reversals in long-term returns (DeBondt & Thaler, 1985) and momentum in short-term returns (Jegadeesh & Titman, 1993; Page 15

Asness, 1995). In 1993, Eugene F. Fama and Kenneth R. French developed a three-factor model, which was able to capture many of the cross-sectional anomalies in average returns (Fama & French, 1996) with a parsimonious extension of the CAPM model to also include HML (high-minus low book-to-market stocks), and SMB (small-minus-big stocks) factors. Acknowledging, however, that their three-factor model was unable to account for the short-term momentum, it fell to Carhart (1997) to extend the Fama-French model further with a momentum factor, later amended by Fama-French as the UMD (up-minus-down) factor. Thus, the four-factor model, alternately described as “consistent with a model of market equilibrium with four risk factors” (Carhart, 1997) and a performance attrition model (further described in [Section 4.1](#)) can be expressed as follows:

$$R_{i,t} - r_{f,t} = \alpha + \beta_{i,m} \cdot (R_{m,t} - r_{f,t}) + \beta_{i,SMB} \cdot R_{SMB} + \beta_{i,HML} \cdot R_{HML} + \beta_{i,UMD} \cdot R_{UMD} + \varepsilon_{i,t}$$

(Equation 3.2.2)

where $R_{i,t} - r_{f,t}$ and $R_{m,t} - r_{f,t}$ are the same as for CAPM, R_{SMB} (small-minus-big) measures the difference between returns on portfolios of small stocks and returns on portfolios of large stocks, R_{HML} (high-minus-low) measures the difference between returns on portfolios of high-book-to-market stocks and returns on portfolios of low-book-to-market stocks, R_{UMD} (up-minus down, also known as winners-minus-losers) measures the momentum effect, and the β_i s measure the excess fund return’s respective sensitivities to the four factors.

Methodology

Compiling summary statistics, examining asset class and fund correlations and calculating volatility ratios formed the starting point to our analysis. Our methodology thereafter was founded on CAPM regressions, adjusted for managed pricing, and then drew on the four-factor model and style analysis to unpack returns attribution.

Interpretation of performance measures across the pre- and post-global financial crisis sub-sample periods (2000 – 2007 and 2008 – 2017 respectively) are discussed in [Section 6](#).

4.1 Traditional portfolio performance evaluation

Measures we used in measuring the performance of the GPFG, FF and CPPIB are outlined below.

Sharpe ratio

Sharpe first proposed the Sharpe ratio in 1966, naming it the return-to-variability ratio. The ratio measures the excess return (the reward) offered by an investment relative to its total volatility (the variability):

$$S_i = \frac{\bar{R}_i - \bar{R}_f}{\sigma_i}$$

(Equation 4.1.1)

where σ_i is the standard deviation of excess portfolio returns. When evaluating Sharpe ratios as a measure of fund performance, a higher Sharpe ratio indicates higher return per unit of variability. It is the appropriate measure to use when comparing entire investment funds (Bodie et al., 2014). As noted by Litterman (2003), maximising the Sharpe ratio is ideally used in the absence of liabilities and a one-period model. The Sharpe ratio ignores the hedging ability of asset-liability streams, and does not maximise utility of an investor who derives utility from both intermediate consumption and final wealth. In our analysis, when applying the Sharpe ratio, returns are net of liability cash flows and thus will take into account the past ability of liability cash flows to hedge cash flows of assets. In addition, utility of consumption of intermediate wealth should not limit the interpretation of Sharpe ratios for historic performance.

Treynor ratio

Treynor introduced the “reward to volatility ratio” in 1965, and this has later become known as the Treynor ratio. The ratio is similar to the Sharpe ratio in that it focuses on excess return, but instead uses systematic risk as to measure risk of the investment (Bodie et al., 2014). The Treynor ratio is calculated as:

$$T_i = \frac{\bar{R}_i - \bar{R}_f}{\beta_{i,m}}$$

(Equation 4.1.2)

A higher Treynor ratio indicates higher return relative to systematic risk of the investment.

Performance regressions

In running our regressions, we sought to find the amount of portfolio return that could be attributed to various risk factors, and if the fund managed to generate any return in excess of what is explained by exposure to risk factors. We began with a simple CAPM regression, explained in [Section 3.2](#):

$$R_{i,t} - R_{f,t} = \hat{\alpha}_i + \hat{\beta}_{i,m}(R_{m,t} - R_{f,t}) + \hat{\epsilon}_{i,t}$$

(Equation 4.1.3)

From this equation, we used $\hat{\beta}_{i,m}$ to determine the amount of exposure the fund has to the market and thus the returns of the fund that can be attributed to market exposure. In this regression $\hat{\alpha}_i$ represents the estimate for Jensen’s alpha, which can be thought of as representing the returns resulting from a manager’s deviation from the benchmark, or the active returns of the portfolio (Jensen, 1968). If the manager is skilful and able to forecast security prices, α_i will be positive. If the opposite is true, α_i will be negative. As noted in Scholz & Wilkins (2005), ranking funds based on α_i can be misleading if a fund uses leverage. For this reason, we focused on estimations of $\hat{\alpha}_i$ not to rank funds, but instead used whether $\hat{\alpha}_i$ was positive and significant to represent whether the manager is adding value.

As was noted in [Section 3.2](#), using a multi-factor model can add explanatory power to a regression by capturing additional risk factors and market anomalies. We extended our regression to include the Fama-French-Carhart factors:

$$R_{i,t} - R_{f,t} = \hat{\alpha}_i + \hat{\beta}_{i,m}(R_{m,t} - R_{f,t}) + \hat{\beta}_{i,SMB} \cdot R_{SMB,t} + \hat{\beta}_{i,HML} \cdot R_{HML,t} + \hat{\beta}_{i,UMD} \cdot R_{UMD,t} + \hat{\epsilon}_{i,t}$$

(Equation 4.1.4)

In extending the analysis to include the factors for *SMB*, *HML* and *UMD*, we wanted to check the robustness of any $\hat{\alpha}_i$ found using a simple CAPM regression. If the $\hat{\alpha}_i$ was attributable to exposure to one the risk factors *SMB*, *HML* or *UMD*, $\hat{\alpha}_i$ will disappear in this second regression. This second regression will also determine whether fund returns can be attributed to the Fama-French-Carhart factors and give an indication of an investment strategy where significant.

Finally, we extended our regression analysis to determine the degree to which allocation to each asset class affected returns. To determine this, we ran variations of the regression:

$$R_{i,t} - R_{f,t} = \hat{\alpha}_i + \hat{\beta}_{i, PubEq}(R_{PubEq,t} - R_{f,t}) + \hat{\beta}_{i, FI}(R_{FI,t} - R_{f,t}) + \hat{\beta}_{i, AA}(R_{AA,t} - R_{f,t}) + \hat{\varepsilon}_{i,t} \quad (\text{Equation 4.1.5})$$

where $\beta_{i,z}$ represents the amount of variation of fund returns that can be explained by covariance with the indicated index for asset class *z*, and R_z represents the returns of the selected index. In the above equation, we denoted asset class *z* public equities with *PubEq*, fixed income with *FI*, and alternative assets with *AA*.

The variations of Equation 4.1.5 include:

- Excluding alternative assets (*AA*) (Equation 4.1.6)
- Adding only property and real estate (*RE*) (Equation 4.1.7)
- Adding indices to represent each of private equity (*PrivEq*), property and real estate (*RE*), infrastructure and timberland (*Infra*), and other alternative assets (*Other*) (Equation 4.1.8)
- Adding a constructed general alternatives index (*GenAlt* - as will be detailed in [Section 5.2](#)) (Equation 4.1.9)

Style regressions

Sharpe (1992) suggested regressing fund returns on indices that represent asset classes in a style regression. Sharpe's focus was on mutual funds which are restricted from taking short positions, thus regression coefficients ($\beta_{i,z}$) were restricted to be zero or positive, and the sum of all coefficients ($\sum \beta_{i,z}$) to be 100 percent. Each coefficient from this restricted regression would then yield the fund's implied allocation to that style, and the R^2 from the regression would represent the return variability attributable to the style indices selected, while remaining variation is attributable to security selection and market timing.

Using Equations 4.1.6 – 4.1.9, we regressed fund returns while restricting $\beta_{i,z} \geq 0$ and $\beta_{i,PublicEq} + \beta_{i,FI} + \dots = 1$. These regressions indicate the allocations in a long-only fund restricted to the assets in the regression equation. We then re-examined the regressions for CPP, this time allowing for short exposures in the style allocation. If a fund invests in a way that is consistent with its stated style, the $\beta_{i,z}$ should be close to the stated allocation to asset class z .

Implications of costs

When evaluating fund performance, it is important that the performance measures selected are indicative of positive excess returns after management fees and transaction costs. Jensen (1968) and Sharpe (1966) both noted that fees can contribute to inferior performance of mutual funds. To ensure the cost of management and transactions do not erode returns, Sharpe ratio, Treynor ratio and alpha must all be positive after the effect of costs. The larger costs are, the more these measures will fall when costs and fees are deducted from returns. However, as noted by Golec (1996), high management fees do not always mean worse performance net of costs, because higher fees can be paid to better managers without eroding profits. The impact of costs and fees is of particular importance in this study, where differing levels of active management are employed in investing, and with FF preferring to outsource to external investment managers.

4.2 Dangers of using traditional performance evaluation for alternative assets

As the asset classes broadly grouped under the heading of ‘alternative assets’ are often illiquid and lack the transparency of the public equity and fixed income markets, we were wary of applying standard methods for assessing risk and returns. Empirical studies for hedge funds (Asness, Krail & Liew, 2001; Getmansky, Lo & Makarov, 2004), real estate and venture capital (Terhaar, Staub & Singer, 2003) have suggested that alternative investments often have unique traits that require adjustments or corrections to properly characterise their risks and expected returns.

Therefore, we utilised adjustments outlined by Asness et al. (2001) to address observed smoothed returns, followed by adjustments derived by Lo (2002, 2008) to properly scale standard deviation and annualise Sharpe ratio estimators in instances of serial correlation.

Detecting illiquidity and smoothed returns

Mindful of Getmansky et al.'s (2004) argument that non-synchronous pricing reactions and/or manager-smoothed returns could lead to serial correlation in returns, we regressed fund returns (GPFG, CPP and FF) against their own lagged values (with one-lag being equivalent to one quarter back). We also checked for serial correlation in the factor returns ($R_{m,t} - r_{f,t}$, $R_{SMB,t}$, $R_{HML,t}$, $R_{UMD,t}$) to distinguish between systematic smoothing (common factors) versus idiosyncratic smoothing (fund-specific) (Lo, 2008).

Building on our simple CAPM regression (Equation 3.2.1) and to reinforce the robustness of our serial correlation findings, we followed Asness et al.'s (2001) methodology to regress excess fund returns against both contemporaneous and lagged excess market returns, expressed as follows:

$$R_{i,t} - r_{f,t} = \alpha_i + \beta_{i,0} \cdot (R_{m,t} - r_{f,t}) + \beta_{i,1} \cdot (R_{m,t-1} - r_{f,t-1}) + \varepsilon_{i,t}$$

$$R_{i,t} - r_{f,t} = \alpha_i + \beta_{i,0} \cdot (R_{m,t} - r_{f,t}) + \beta_{i,1} \cdot (R_{m,t-1} - r_{f,t-1}) + \beta_{i,2} \cdot (R_{m,t-2} - r_{f,t-2}) + \varepsilon_{i,t}$$

... (Equation 4.2.1)

where $\beta_{i,0}$ is the observed fund return's exposure to the contemporaneous excess market return, $\beta_{i,1}$ is the exposure to the one-lag excess market return, etc.

Furthermore, we attempted to distinguish between unintentional serial correlation (stale pricing due to illiquidity) versus intentional managed pricing by dissecting lagged betas into 'up market' lagged betas and 'down market' lagged betas, expressed as follows:

$$R_{i,t} - r_{f,t} = \alpha_i + \beta_{i,0}^{pos} \cdot (R_{m,t} - r_{f,t})^{pos} + \beta_{i,0}^{neg} \cdot (R_{m,t} - r_{f,t})^{neg} + \varepsilon_{i,t}$$

$$R_{i,t} - r_{f,t} = \alpha_i + \beta_{i,0}^{pos} \cdot (R_{m,t} - r_{f,t})^{pos} + \beta_{i,1}^{pos} \cdot (R_{m,t-1} - r_{f,t-1})^{pos} + \beta_{i,0}^{neg} \cdot (R_{m,t} - r_{f,t})^{neg} + \beta_{i,1}^{neg} \cdot (R_{m,t-1} - r_{f,t-1})^{neg} + \varepsilon_{i,t}$$

... (Equation 4.2.2)

where $\beta_{i,1}^{pos}$ is the exposure to the one-lag excess up market return, $\beta_{i,1}^{neg}$ is the exposure to the one-lag excess down market return, and so on up to lag k . Asness et al. (2001) contended that exposure to lagged excess market return would be significant and symmetrical for both up and down markets if returns were affected

by unintentional stale pricing. However, if the funds' returns were driven by intentional managed pricing, lagged betas in down markets would be more significant than for up markets.

In addition, we examined volatility ratios (VR) for the funds:

$$VR = \frac{\text{Annual volatility}}{\text{Annualised quarterly volatility}}$$

where $VR \gg 1$ indicates stale or managed pricing, as annualised volatility should approximate annual volatility. We nonetheless noted that especially for global public equity and fixed income markets, which are often subject to very stringent disclosure requirements, $VR > 1$ could also occur where there is momentum in the market returns.

4.3 Adjustments in the presence of managed returns

AKL adjustment

Where fund(s) were observed to have significant exposure to lagged excess market returns, we traced back the number of lags (k) it would be appropriate to make adjustments for. We then followed Asness et al.'s (2001) method of summing the lagged betas.

$$\beta_i^{true} = \sum_{j=0}^k \beta_{i,j}^{obs}$$

(Equation 4.3.1)

where $\beta_{i,j}^{obs}$ is the market beta of observed returns at lag j , and k is the number of significant lags of market beta. This is hereafter referred to as the 'AKL adjustment'.

Lo adjustment

To adjust the quarterly and annual Sharpe ratios, we proceeded with the methodology suggested by Lo (2002, 2008) to compute scaling factors for standard deviation and the annualised Sharpe ratio. This is hereafter referred to as the 'Lo adjustment'. Lo (2002, 2008) noted that stale pricing and/or smoothed returns often leads to distorted Sharpe ratios:

$$SR_i^{obs} \equiv \frac{E[R_{i,t}^{obs}]}{\sqrt{\text{Var}[R_{i,t}^{obs}]}} \geq SR_i^{true} \equiv \frac{E[R_{i,t}^{true}]}{\sqrt{\text{Var}[R_{i,t}^{true}]}}$$

(Equation 4.3.2)

Lo Standard Deviation Adjustment

Lo then proposed that the distorted Sharpe ratio is due to the observed contemporaneous return $R_{i,t}^{obs}$ being the weighted sum of contemporaneous and lagged true returns:

$$\begin{aligned}
 R_{i,t}^{obs} &= \theta_{0,i} \cdot R_{i,t}^{true} + \theta_{1,i} \cdot R_{i,t-1}^{true} + \theta_{2,i} \cdot R_{i,t-2}^{true} + \dots \\
 \theta_{j,i} &\in [0,1] && j = 0, \dots, k \\
 1 &= \theta_{0,i} + \theta_{1,i} + \dots + \theta_{k,i}
 \end{aligned}$$

(Equation 4.3.3)

In order to obtain the estimators for θ_j , we followed Lo’s (2008) use of true and observed betas from the AKL adjustment (Equation 4.3.1):

$$\widehat{\theta}_{i,j} = \frac{\widehat{\beta}_{i,j}^{obs}}{\widehat{\beta}_{i,t}^{true}}$$

(Equation 4.3.4)

We next determined the factor (c_i) by which we needed to scale returns to arrive at a more appropriate standard deviation (σ_i), which affects Sharpe ratio, Treynor ratio, beta (β_i) and alpha (α_i).

$$c_i = 1 / \sqrt{\theta_{0,i}^2 + \dots + \theta_{k,i}^2}$$

(Equation 4.3.5)

Lo Annualised Sharpe Ratio Adjustment

In addition, Lo (2002, 2008) noted the presence of additional bias when quarterly Sharpe ratios are annualised by multiplying $\sqrt{4}$ in instances of non-IID (independent and identically distributed) returns, as is the case when there is serial correlation.

For non-IID returns, the adjustment factor for time-aggregated Sharpe ratios is generally not \sqrt{q} (where $q = 4$ to annualise quarterly returns) but also a function of the first ($q - 1$) autocorrelations of returns. Thus the quarterly Sharpe ratio SR is scaled by the factor $\eta(q)$ to compute the annualised quarterly Sharpe ratio $SR(q)$:

$$\begin{aligned}
 \widehat{SR}_i(q) &= \widehat{\eta}_{i,z}(q) \cdot \widehat{SR}_i \\
 \widehat{\eta}_{i,z}(q) &= \frac{q}{\sqrt{q + 2 \cdot \sum_{k=1}^{q-1} (q - k) \cdot \widehat{\rho}_{k,i,z}}}
 \end{aligned}$$

(Equation 4.3.6)

where $\widehat{\rho}_k$ is the sample’s k th-order autocorrelation coefficient and $q = 4$.

Where a fund was observed to exhibit autocorrelation, the relevant scaling factors (c_i), and $\eta_{i,z}(q)$ were calculated for total returns, total alternative asset returns as well as individual alternative asset classes (z).

4.4 Interpreting results

We used a statistical significance level of 5 percent when interpreting the significance of the alpha and beta coefficients resulting from the regressions.

$$H_0: \alpha_i \leq 0 \quad H_1: \alpha_i > 0$$

$$H_0: \beta_i = 0 \quad H_1: \beta_i \neq 0$$

We also took particular note where the p-value was very close to the 5 percent significance level and we were unable to reject or accept the null hypothesis with more definiteness.

Determining the influence of alternative assets

With our focus on whether the funds have been significantly influenced by the addition of alternative asset classes, we also inspected whether the weighted removal of alternative assets from the funds results in changes to the of the α_i and the degree to which their market exposure (β_i) changes. When alternative assets are included in portfolio returns, the portfolio returns are calculated as:

$$R_{i,t} = \sum_{z=1}^N w_{z,t} \cdot R_{z,t}$$

(Equation 4.4.1)

where

$$w_{z,t} = \frac{V_{z,t}}{\sum_{z=0}^Z V_{z,t}}$$

(Equation 4.4.2)

and $V_{z,t}$ is the market value of asset z at time t and $\sum V_{z,t}$ is the sum of the value of all asset classes. To examine fund performance excluding alternative asset investments, we removed all investment values from alternative investments from each of GPFG's, CPP's and FF's portfolios such that $V_z = 0$ for all alternative asset classes. In doing so, the size of each fund's portfolio is decreased by the value that was invested in alternative assets, and the fund return is equal to:

$$R_{i,t} = \frac{V_{PubEq,t}}{V_{PubEq,t} + V_{FI,t}} \cdot R_{PubEq,t} + \frac{V_{FI,t}}{V_{PubEq,t} + V_{FI,t}} \cdot R_{FI,t}$$

(Equation 4.4.3)

We also investigated the significance of any changes to α_i and β_i when alternative assets are excluded from the fund portfolio. Demonstrating with the simple CAPM regression from Equation 3.2.1 and accounting for the weight of alternative assets in the original fund portfolios:

$$\begin{aligned} (R_{i,t}^{All} - r_{f,t}) - (R_{i,t}^{No Alt} - r_{f,t}) \\ = (\alpha_i^{All} - \alpha_i^{No Alt}) + (\beta_{i,0}^{All} - \beta_{i,0}^{No Alt}) \cdot (R_{m,t} - r_{f,t}) + \varepsilon_{i,t} \end{aligned} \quad (\text{Equation 4.4.4})$$

This then simplifies down to:

$$R_{i,t}^{Diff} = \delta_i^{Diff} + \gamma_{i,0}^{Diff} \cdot (R_{m,t} - r_{f,t}) + \varepsilon_{i,t} \quad (\text{Equation 4.4.5})$$

This procedure is then replicated and extended for Equations 4.2.4 and 4.2.5 as follows:

$$\begin{aligned} R_{i,t}^{Diff} &= \delta_i^{Diff} + \gamma_{i,0}^{Diff} \cdot (R_{m,t} - r_{f,t}) + \gamma_{i,1}^{Diff} \cdot (R_{m,t-1} - r_{f,t-1}) + \varepsilon_{i,t} \\ R_{i,t}^{Diff} &= \delta_i^{Diff} + \gamma_{i,0}^{Diff} \cdot (R_{m,t} - r_{f,t}) + \gamma_{i,1}^{Diff} \cdot (R_{m,t-1} - r_{f,t-1}) + \gamma_{i,2}^{Diff} \\ &\quad \cdot (R_{m,t-2} - r_{f,t-2}) + \varepsilon_{i,t} \\ &\quad \dots \\ &\quad \dots \end{aligned} \quad (\text{Equation 4.4.6})$$

$$R_{i,t}^{Diff} = \delta_i^{Diff} + \gamma_{i,0}^{Diff,pos} \cdot (R_{m,t} - r_{f,t})^{pos} + \gamma_{i,0}^{Diff,neg} \cdot (R_{m,t} - r_{f,t})^{neg} + \varepsilon_{i,t}$$

$$\begin{aligned} R_{i,t}^{Diff} &= \delta_i^{Diff} + \gamma_{i,0}^{Diff,pos} \cdot (R_{m,t} - r_{f,t})^{pos} + \gamma_{i,1}^{Diff,pos} \cdot (R_{m,t-1} - r_{f,t-1})^{pos} \\ &\quad + \gamma_{i,0}^{Diff,neg} \cdot (R_{m,t} - r_{f,t})^{neg} + \gamma_{i,1}^{Diff,neg} \cdot (R_{m,t-1} - r_{f,t-1})^{neg} \\ &\quad + \varepsilon_{i,t} \\ &\quad \dots \end{aligned} \quad (\text{Equation 4.4.7})$$

Data

5.1 Fund data

Our primary data set consisted of returns (gross and net of costs) collated from quarterly and annual reports from GPF, CPP and FF. Within these returns, we broadly grouped (1) public equities and (2) fixed income whilst splitting alternative asset classes into its components in the following delineation: (3) private equity, (4) infrastructure & timberland, (5) property & real estate, and (6) other alternative assets. In addition, (3) to (6) were summed to form a ‘total alternative assets’ category. In the below fund sections, we made note of the additional assumptions required to obtain comparable returns data.

We noted that the funds do not provide data on re-allocation of assets under management (AUM) between asset classes and re-investment ratios of distributions.

GPF

Data for GPF was sourced from annual and quarterly reporting, as well as the publicly available returns file provided by NBIM.

Returns	Quarterly returns were calculated from quarterly changes in net asset value per asset class (1) – (6), net of contributions and withdrawals. In the years 2000 and 2001, quarterly reporting is not available in English, and so we used NBIM’s monthly return disclosure for these years and converted returns to quarterly. In January 2001, NBIM reclassified 73 million NOK of publicly-listed real estate investments, now disclosing these investments as public equity (previously real estate), and thus the net asset value used to calculate returns for public equity and real estate in Q1 2017 are adjusted for this reclassification.
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Contributions and withdrawals	For most years in our sample, NBIM discloses how contributions to the fund have been allocated across asset classes at each year-end. NBIM also discloses net contributions to the fund quarterly. To allocate net contributions and withdrawals to asset classes in each
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quarter, we used the relative annual allocation. In 2016 and 2017 withdrawals from the fund are only provided on a total fund basis, and thus we assumed the withdrawal is equally split between fixed income and public equity.

Costs Costs are provided on a total fund basis and are not split by asset class. When excluding alternatives from the portfolio, median cost as a percentage of investments is calculated for each subsample period.

Other adjustments GPFPG had a tactical asset allocation portfolio in 2001 and 2002, including both public equity and fixed income securities and amounting to 0.41 percent of AUM on average in these years. Changes in net asset value for this asset class appear to be driven by reallocation, and thus returns are treated as non-meaningful and are excluded from the portfolio.

CPP

Data for CPP investments was sourced from CPPIB public disclosure in quarterly and annual reports.

Returns Quarterly returns were calculated as investment income divided by investment value per asset class (1) – (6). CPPIB discloses investment income per asset classes (1) – (6) annually and is adjusted to quarterly by allocating 25 percent of annual investment income to each quarter in the year. This is true for all asset classes except for fixed income, which is reported quarterly. Investment income includes realised gains and losses, changes in unrealised gains and losses, interest income, and dividends. CPPIB groups all equities (public and private) in 2016 and 2017 reporting. We therefore assumed the investment income to be split equally between public and private equity, consistent to relative

income in previous years where necessary granularity is provided.

Contributions
and withdrawals

CPPIB does not provide detailed information on how contributions and withdrawals to and from the fund are allocated amongst asset classes. Our calculation of returns provides a solution to this lack of data, whereby we assumed investment income is based on assets invested at the beginning of the quarter and any reallocations occur at the last moment of the quarter.

Costs

Costs were sourced from CPPIB's disclosure on investment fees and transaction costs. CPPIB has not provided consistent granularity of investment fees and transaction costs over our study period, grouping all equities (public and private) in 2016 and 2017. We therefore assumed investment costs and transaction fees to be allocated 75 percent to private equity and 25 percent to public equity, consistent with relative costs in previous years where necessary granularity is provided.

Additionally, CPPIB uses leverage in its investment portfolio. To estimate interest costs, we used 1-, 5-, and 10-year interest rates for Canadian fixed income instruments, matching the maturity of debt financing, plus a margin of 25 basis points per year. Where no debt maturity is provided, the 10-year interest rate is used.

Future Fund

Data for FF investments was sourced from FF public disclosure in quarterly portfolio updates and annual reports.

Returns

Quarterly returns were calculated from quarterly changes in net asset value per asset class (1) – (6).

Contributions and
withdrawals

There have been no additional contributions to the FF, nor have there been withdrawals by the government, so this adjustment was not required.

Costs FF does not provide breakdowns of the costs of the various asset classes either annually or by other time periods. Therefore, we sourced standardised average investment costs (percent) per asset class for U.S. defined benefit pension funds (CEM Benchmarking, 2017) using data collected from 1998 – 2015, aligning well with our period of study.

General adjustments to fund data

As we compared returns against USD-denominated indices and style portfolio(s), we exchanged gross and net returns from their domestic currencies (NOK, CAD and AUD for GPFG, CPP and FF respectively) to USD. We then converted all returns data to log returns and excluded returns > 400 percent as not meaningful (displayed as ‘*n.m.f*’ in the model). To come to the excess fund returns, we deducted the quarterly global risk-free rate discussed in [Section 5.2](#) ‘Kenneth R. French Data Library’.

Comparison of 2000 – 2007 versus 2008 – 2017

Given that our research question investigates the effect of the global financial crisis, we divided our data into two sub-sample periods: pre- and post-global financial crisis. Splitting the data into 2000 – 2007 and 2008 – 2017 also took into account two other key facts: (1) FF began investing in alternative assets in the second half of 2007, and (2) in 2006, CPPIB changed their investment strategy, henceforth actively diversifying investments by asset class and geography, but the compensation scheme for the updated active investment strategy was not approved until 2007. We therefore assumed 2007 to be a transitional year and that returns from 2008 onwards would be more fully representative of the current ‘Canada model’ and ‘Australia model’ as described in [Sections 2.3](#) and [2.4](#) respectively.

Given the sparsity of FF data pre-2008 (the FF was established in May 2006 and held almost all assets in cash until second half of 2007), FF was excluded from the 2000 - 2007 subsample as findings would not be meaningful for FF in this period.

5.2 Supplementary data

Our primary data set was supplemented with benchmark data and currency exchange rates sourced from the Bloomberg, the Kenneth R. French Data Library

and the updated Doeswijk, Lam and Swinkels (2014) global market portfolio data. The data was used as benchmark indices, benchmark factors and to construct our own benchmark indices and fund benchmarks. We noted that this data is more comparable with our gross-of-cost returns fund data but compare against both gross and net of cost returns for completeness.

Kenneth R. French data library

We sourced the global returns for the three factors (R_{SMB} , R_{HML} , R_{UMD}) as well as the quarterly global risk-free rate ($r_{f,t}$) from the Kenneth R. French Data Library. We did not use the Fama-French data for excess market return as it only included developed countries. To maintain consistency with our benchmark indices and the investment portfolios of the funds, we used market return from the MSCI All Country World Index (see following subsection ‘Bloomberg Database’) and deducted the Fama-French risk-free rate to arrive at the excess market return ($R_{m,t} - r_{f,t}$) from Equation 3.2.2.

Doeswijk, Lam and Swinkels global market portfolio

We used Doeswijk et al.’s (2014) data, updated to 2017, to source global market capitalisation for private equity and real assets. This was incorporated in the construction of our broad, global ‘General Alternatives’ benchmark index.

Bloomberg database

We focused on global benchmark indices, given the funds’ wide global exposure. Returns data was sourced from 1999 – 2017 for the following (where available) and excess benchmark returns were calculated by deducting the global risk-free rate discussed in the above sub-section (‘Kenneth R. French Data Library’).

- | | |
|-------------------|---|
| (1) Public Equity | MSCI All Country World Index (<i>MXWD Index</i>) covering equity returns in 23 developed and 24 emerging markets. |
| (2) Fixed Income | Bloomberg Barclays Global-Aggregate Bond Index (<i>LEGATRUU Index</i>), covering global investment grade debt from 24 local currency markets. |

- (3) Private Equity LPX Composite (*LPXCMPTR Index*), covering all major private equity companies listed on global stock exchanges.
From 1999 – 2001, where data for the LPX Composite was unavailable, returns were used from LPX50, covering the largest private equity companies listed on global stock exchanges.
- (4) Infrastructure & Timberland From 2007 – 2017, market-capitalisation weighted composite of the S&P Global Infrastructure Index (*SPGTINTR Index*), covering 75 companies from around the world chosen to represent the listed infrastructure universe, and S&P Global Timber & Forestry Index (*SPGTTFN Index*), covering 25 of the largest publicly traded companies engaged in upstream supply chain of forests and timberlands.
Earlier, when market capitalisation data was unavailable, the S&P Global Infrastructure Index was used on its own from 2002 – 2006.
From 1999 – 2001, when S&P Global Infrastructure Index returns were unavailable and there were very few relevant benchmark indices with available data, we used the Alerian MLP Infrastructure Index (*AMZI Index*), covering energy infrastructure MLPs.
- (5) Property & Real Estate FTSE NAREIT All Equity REITS Index (*FNERTR Index*), covering all tax qualified REITs listed in the NYSE, AMEX, and NASDAQ national market.
- (6) Other alternative assets This asset class was only applicable to CPP and FF, described as pursuing ‘absolute return strategies’. We therefore used HFRX Global Hedge Fund Index (*HFRXGL Index*) as the closest proxy, covering all eligible hedge fund strategies.
- General alternative assets We were unable to find a general, global alternative assets benchmark index and therefore constructed market-capitalisation weighted composite of our Private Equity index above and a Real Assets index. Market

capitalisation weights are sourced from Doeswijk et al. (2014), updated to 2017.

The Real Assets index is comprised of the S&P Real Assets Index (*SPRAUT Index*) from second half of 2005 – 2017, covering a diverse array of financial assets or assets whose value derive from physical underlying assets. From 1999 – first half of 2005, when data for the S&P Real Assets Index were unavailable, returns were used from GPR General Index (*GGENGLOB Index*), covering all listed real estate companies that comply with Global Property Research’s criteria.

Bloomberg ticker in brackets. 1999 data was only used in the calculation of lagged returns.

5.3 Creation of fund benchmarks

Each fund’s benchmark return ($R_{i,t}^{benchmark}$) is computed as follows:

$$R_{i,t}^{benchmark} = \sum (asset\ weight_{i,z,t} \cdot benchmark\ index\ return_{z,t})$$

Where $asset\ weight_{i,z,t}$ is the percent weight for asset class z per quarter, and $benchmark\ index\ return_{z,t}$ is the benchmark index return for asset class z per quarter. Comparison of the funds against their specific benchmark is discussed in Section 6.4.

Results and Analysis

We began by examining evidence of stale pricing and/or manager-smoothed returns and performed the relevant adjustments ([Sections 6.1](#) and [6.2](#)). We then observed the diversification benefits of alternative assets, using correlation as a high-level indicator ([Section 6.3](#)) and reviewed benchmark summary statistics ([Section 6.4](#)).

In [Sections 6.5](#), [6.6](#) and [6.7](#), we delved into GPFG, FF and CPP respectively: first inspecting summary statistics and then building the foundation of analysis on the simple CAPM regression model. For CPP where post-adjustment returns still showed signs of stale pricing and/or manager-smoothed returns, we extended the CAPM approach further with lags on excess market returns ([Section 6.7.2](#)) and used an asymmetric CAPM approach with lags on excess market returns ([Section 6.7.3](#)). Given that the ‘true’ source of return smoothing was yet undiscovered, we reinforced our CPP analyses with a factor approach ([Section 6.7.4](#)) and a benchmark approach using performance regressions and style regressions ([Section 6.7.5](#)). For completeness, we also ran these analyses for GPFG and FF and see results that are largely in line with expectations. Finally, we summarised our overall findings in [Section 6.8](#), that alternative assets have the potential to offer both diversification benefits and the capacity to smooth portfolio returns artificially. The latter is particularly relevant in conjunction with internal fund management.

It is noteworthy that comparison of results gross and net of costs yielded very small changes (and no change in whether variables are deemed significant). Therefore, this section focused on gross of cost results unless explicitly mentioned.

6.1 Adjustments for smoothed returns

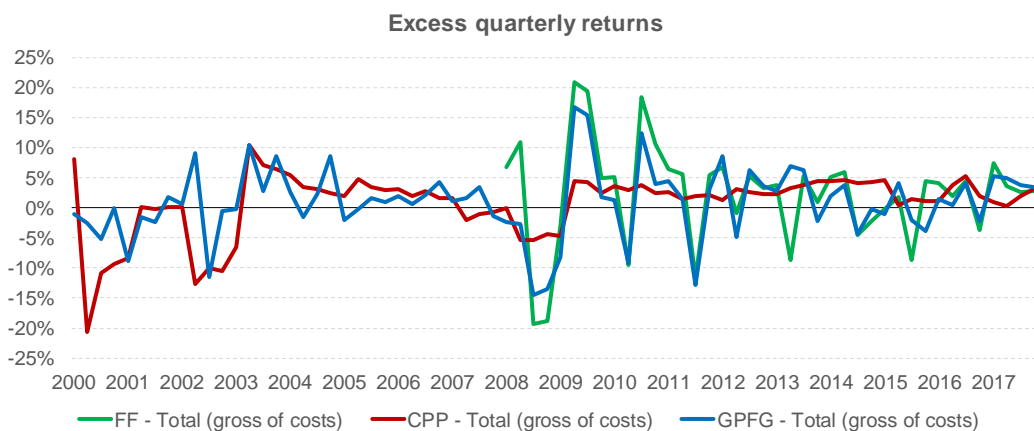


Figure 6.1.1: Excess quarterly returns for FF, CPP and GPFG

As discussed in [Section 4.2](#), we noted the likelihood of our results being biased by smoothed returns and therefore began with a visual inspection of the excess fund

returns over time (Figure 6.1.1), calculated volatility ratios per fund and per fund asset class, and tested for serial correlation ([Appendix A](#)).

From Figure 6.1.1, we observed that the volatility of CPP’s quarterly excess returns appear to be too low relative to their peers (GPF and FF), particularly after CPP updated their investment strategy, as seen in subsample 2. This was further corroborated by examining VR ($VR \gg 1$ for CPP) and testing for serial correlation, both suggesting that CPP returns are serially correlated. Nonetheless, we did note that although FF’s overall returns have $VR < 1$ and are not significantly serially correlated, their alternative asset classes do show $VR \gg 1$.

We proceeded with the Lo standard deviation adjustment for overall CPP excess returns as outlined in [Section 4.3](#), using the $\widehat{\beta}_{i,t}^{true}$ and $\widehat{\beta}_{i,t}^{obs}$ obtained from lagged CAPM regressions for $j = 0, \dots, k$ (Equation 4.2.1) to determine the scaling factor (c_{CPP}) with which we adjusted CPP returns. To arrive at a more appropriate annualised Sharpe ratio for CPP, we then followed the Lo annualised Sharpe ratio adjustment to compute the relevant scaling factor, $\eta_{CPP}(q)$ (Equation 4.3.6). This procedure was repeated for instances where CPP’s individual alternative asset classes (z) also demonstrated significant serial correlation ([Appendix A](#)).

Overall, these adjustments to partially counter CPP’s observed serial correlation were implemented for CPP’s total returns, total alternative asset returns as well as relevant individual alternative asset classes. The following analysis and discussion of results shall proceed in a ‘post-Lo adjustment’ setting.

6.2 Re-examination of serial correlation

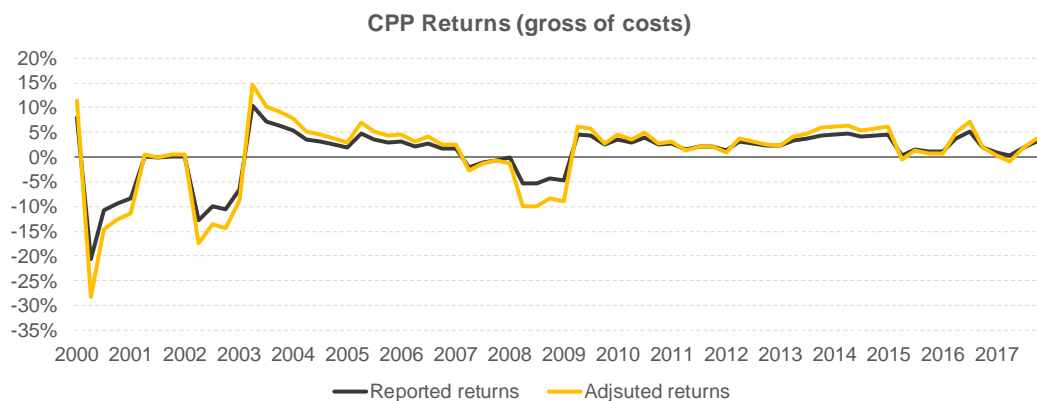


Figure 6.2.1: CPP returns as reported and after adjustment for smoothed returns

We caution that the Lo adjustment was not intended to resolve or eliminate serial correlation, but rather, adjust the standard deviation of CPP returns and performance measurements for comparison against peers. As seen in Figure 6.2.1,

there remains evidence of smoothed returns upon visual inspection. Thus, it is worthy to re-examine serial correlation in the ‘post-Lo adjustment’ setting as well.

We saw that CPP returns still exhibit serial correlation, as expected ([Appendix B](#)). To test our hypothesis that this serial correlation is largely due to the alternative assets part of their investment portfolio, we removed alternative assets from CPP assets ([Section 4.4](#)) and compared the serial correlation test results with and without alternatives. Despite the decrease in β (i.e. at time t , CPP returns’ sensitivity to CPP returns at $t - 1$ has fallen), CPP returns are still significantly serially correlated without alternative assets. However, the decrease in β is statistically significant, and we revisit this throughout our discussion and analysis.

Turning our attention to factor returns, our primary focus was the excess (public equity) market return. Here, the presence of statistically insignificant serial correlation in the excess market return indicated the lack of a momentum effect, which is inconsistent with the broader literature (Jegadeesh & Titman, 1993; Asness, 1995; Fama & French, 2012). We propose that the inconsistency could be related to regional differences in our data set (global equity index, including developing markets) versus Jegadeesh and Titman (1993; NYSE), Asness (1995; US) and Fama and French (2012; developed markets North America, Europe, Japan and Asia Pacific), or the discrepancy may partially be due to our test of one lag (i.e. one quarter back) versus Asness’ (1995) specification of one-year momentum strategy.

6.3 Correlations

As mentioned in [Section 2.5](#), one reason for adding alternative assets to a portfolio is if inclusion of the asset diversifies returns of the existing portfolio. We focused first on correlation as a high-level indication of diversification benefits of alternative assets. To contrast the pre- and post-global financial crisis returns, we divided the data into two subsample periods: 2000 - 2007 and 2008 - 2017 as discussed in [Section 5.1](#) and examined the funds’ correlations with various asset class benchmark indices (summarised in [Section 5.2](#) ‘Bloomberg Database’) and the inter-asset class correlations. The full correlations table for both subsample periods can be found in [Appendix C](#).

Subsample 1: We saw broadly positive correlations, apart from Fixed Income 2000 - 2007 (negative correlations with Public Equity, Private Equity and CPP excess fund returns)

Subsample 2: Correlations have broadly increased, particularly between 2008 - 2017 Public Equity and Fixed Income with alternative asset classes. The notable exception to this is Fixed Income and Other Alternatives (correlation decreased). That correlations across asset classes have increased since the global financial crisis is consistent with other studies (IMF, 2015). There remains a negative correlation between Fixed Income and Private Equity, but much weaker than pre-crisis.

Results of this analysis indicate that the inclusion of alternative assets in a portfolio would have limited contribution to the diversification of returns.

6.4 Summary statistics

To outline key features of our data, we reviewed the Summary Statistics below for the benchmark indices (summarised in [Section 5.2 ‘Bloomberg Database’](#)) across subsample 1: 2000 – 2007, and subsample 2: 2008 – 2017. Note that all numbers (and thus returns) have been converted to a common currency of US dollar.

Table 6.4.1: Summary statistics for indices and constructed benchmarks

	Entire sample				Subsample 1: 2000-2007				Subsample 2: 2008-2017			
	Before costs				Before costs				Before costs			
	Mean	Std Dev	Sharpe	Sharpe (Ann.)	Mean	Std Dev	Sharpe	Sharpe (Ann.)	Mean	Std Dev	Sharpe	Sharpe (Ann.)
Excess quarterly returns												
Benchmark indices												
Public equity	0.17%	8.81%	0.02	0.04	-0.27%	8.22%	-0.03	-0.07	0.53%	9.35%	0.06	0.11
Fixed income	0.75%	3.01%	0.25	0.50	0.82%	2.94%	0.28	0.56	0.69%	3.10%	0.22	0.44
Other												
Alternative assets												
Private equity	-0.03%	15.28%	0.00	0.00	-1.64%	14.04%	-0.12	-0.23	1.25%	16.27%	0.08	0.15
Infrastructure & timberland	2.73%	7.91%	0.35	0.69	5.13%	5.53%	0.93	1.85	0.82%	9.01%	0.09	0.18
Property & real estate	2.36%	11.04%	0.21	0.43	3.07%	7.37%	0.42	0.83	1.80%	13.34%	0.13	0.27
Other	0.34%	3.32%	0.10	0.21	0.99%	2.52%	0.39	0.79	-0.18%	3.80%	-0.05	-0.09
General alternatives index	1.50%	8.36%	0.18	0.36	1.96%	6.15%	0.32	0.64	1.13%	9.85%	0.11	0.23
Australia benchmark	1.02%	4.59%	0.22	0.44					1.02%	4.59%	0.22	0.44
Canada benchmark	0.23%	7.10%	0.03	0.07	-0.65%	7.85%	-0.08	-0.16	0.93%	6.45%	0.14	0.29
Norway benchmark	0.54%	4.79%	0.11	0.23	0.42%	3.65%	0.11	0.23	0.64%	5.56%	0.11	0.23

Table 6.4.2: Summary statistics for CPP and GPFG: 2000-2007

	Subsample 1: 2000-2007											
	Before costs					After costs					Asset weights	
	Mean	Std Dev	Sharpe	Sharpe (Ann.)	Treynor's	Mean	Std Dev	Sharpe	Sharpe (Ann.)	Treynor's	Average	Median
Excess quarterly returns												
Canada												
Public equity	0%	7%	-0.04	-0.08		0%	7%	-0.04	-0.08		77%	83%
Fixed income	1%	6%	0.20	0.39		1%	6%	0.20	0.39		21%	23%
<i>Alternative assets</i>												
Private equity	2%	6%	0.33	0.38		2%	6%	0.32	0.37		5%	5%
Infrastructure & timberland	1%	3%	0.27	0.33		1%	3%	0.26	0.32		1%	0%
Property & real estate	-3%	25%	-0.13	-0.17		-3%	25%	-0.13	-0.17		3%	2%
Other	8%	3%	n.m.f.	n.m.f.		6%	3%	n.m.f.	n.m.f.		0%	0%
Total alternatives	1%	10%	0.07	0.09		1%	10%	0.07	0.08		7%	7%
Total return	-1%	10%	-0.07	-0.09	-0.01	-1%	10%	-0.07	-0.10	-0.01	100%	100%
Norway												
Public equity	0%	9%	-0.01	-0.01		-	-	-	-		40%	40%
Fixed income	1%	5%	0.27	0.55		-	-	-	-		59%	59%
<i>Alternative assets</i>												
Private equity	-	-	-	-		-	-	-	-		-	-
Infrastructure & timberland	-	-	-	-		-	-	-	-		-	-
Property & real estate	-	-	-	-		-	-	-	-		-	-
Other	-	-	-	-		-	-	-	-		-	-
Total alternatives	-	-	-	-		-	-	-	-		0%	0%
Total return	1%	5%	0.18	0.36	0.02	1%	5%	0.17	0.33	0.02	100%	100%

Table 6.4.3: Summary statistics for FF, CPP and GPFG: 2008-2017

	Subsample 2: 2008-2017											
	Before costs					After costs					Asset weights	
	Mean	Std Dev	Sharpe	Sharpe (Ann.)	Treynor's	Mean	Std Dev	Sharpe	Sharpe (Ann.)	Treynor's	Average	Median
Excess quarterly returns												
Australia												
Public equity	3%	14%	0.22	0.44		3%	14%	0.21	0.43		32%	31%
Fixed income	0%	14%	-0.03	-0.05		0%	14%	-0.03	-0.07		53%	59%
<i>Alternative assets</i>												
Private equity	8%	9%	0.92	1.84		7%	9%	0.86	1.72		2%	2%
Infrastructure & timberland	7%	11%	0.65	1.30		7%	11%	0.63	1.25		2%	2%
Property & real estate	7%	18%	0.37	0.74		6%	18%	0.35	0.71		3%	2%
Other	7%	18%	0.40	0.80		7%	18%	0.39	0.77		7%	5%
Total alternatives	8%	14%	0.55	1.11		7%	14%	0.53	1.06		14%	11%
Total return	2%	9%	0.27	0.54	0.03	2%	9%	0.25	0.51	0.03	100%	100%
Canada												
Public equity	2%	6%	0.29	0.59		2%	6%	0.28	0.57		31%	30%
Fixed income	1%	2%	0.50	1.00		1%	2%	0.45	0.90		41%	41%
<i>Alternative assets</i>												
Private equity	3%	5%	0.57	0.65		3%	6%	0.50	0.57		16%	17%
Infrastructure & timberland	2%	2%	0.93	1.15		2%	3%	0.87	1.07		6%	6%
Property & real estate	2%	4%	0.46	0.60		2%	4%	0.41	0.53		10%	11%
Other	0%	1%	0.02	0.02		0%	1%	-0.02	-0.02		4%	5%
Total alternatives	2%	4%	0.54	0.67		2%	4%	0.48	0.59		36%	39%
Total return	2%	4%	0.45	0.61	0.04	2%	4%	0.39	0.52	0.03	108%	109%
Norway												
Public equity	1%	12%	0.06	0.13		-	-	-	-		58%	61%
Fixed income	1%	11%	0.08	0.15		-	-	-	-		41%	38%
<i>Alternative assets</i>												
Private equity	-	-	-	-		-	-	-	-		-	-
Infrastructure & timberland	-	-	-	-		-	-	-	-		-	-
Property & real estate	-3%	30%	-0.11	-0.22		-	-	-	-		1%	0%
Other	-	-	-	-		-	-	-	-		-	-
Total alternatives	-3%	30%	-0.11	-0.22		-	-	-	-		1%	0%
Total return	1%	7%	0.16	0.33	0.02	1%	7%	0.16	0.32	0.02	100%	100%

Benchmark indices

We noted that public and private equity indices appear to have very low Sharpe ratio over the entire sample period, 2000-2017, driven by negative average excess return over subsample 1. Relative to equity indices, alternative asset indices appear to be an attractive investment based on Sharpe ratio for the entire sample period. Alternative asset indices have some of the highest Sharpe ratios in subsample 1, save for private equities which have negative excess return as aforementioned. However, performance of alternative assets is more tempered in subsample 2, with lower absolute Sharpe ratios for each index, yet remaining more attractive than public equities on this measure. The only exception is the Other index (hedge fund

index) which exhibited negative Sharpe ratio. Public equities had an annualised Sharpe ratio of 0.11 across subsample 2, despite the fact that the global financial crisis is included in subsample 2. Finally, we noted the stability of the fixed income index’s Sharpe ratio, remaining around 0.50 for both subsamples. Comparing this to our findings from [Section 6.3](#), we saw that although offering limited diversification benefit, the inclusion of alternative assets in a portfolio may still be justified with their attractive return-to-risk characteristics.

6.5 Government Pension Fund Global (GPFG)

GPFG began investing in alternative assets (real estate) in 2011, but this asset class comprises only 2.5 percent of their portfolio as of December 31, 2017. At a high-level examination of summary statistics in Tables 6.4.2 and 6.4.3, the inclusion of real estate does appear to have contributed to portfolio returns but with a negative average return. However, this negative average return is attributable to seven (of total 27) quarters where losses exceeded 20 percent for real estate, which has also contributed to high standard deviation. The overall fund Sharpe ratio in subsample 2 is higher than that of any individual asset class (Table 6.4.3) and the constructed GPFG benchmark (Figure 6.5.1), demonstrating that their investments have diversified portfolio returns.



Figure 6.5.1 GPFG vs. constructed benchmark excess quarterly returns

A CAPM approach

We started by noting that based on the simple CAPM results below (Table 6.5.1), GPFG has significant exposure to the market ($\beta_{m,0}$), as expected. GPFG only has positive and significant alpha pre-crisis and before cost, and all other specifications of α_{GPFG} are insignificant, which can be expected given their focus on passive investing and beta returns. We also saw an increase in GPFG’s R^2 from 0.53 to 0.82 and $\beta_{m,0}$ from 0.41 to 0.66 pre- and post-crisis, in line with their increasing

allocation to public equity. Upon removing alternative assets from the GPFG portfolio and focusing on the 2008 – 2017 period, we identified that exposure to contemporaneous excess market return ($\beta_{m,0}^{No Alt}$) increases slightly, as expected from an increased relative investment in public equity.

Table 6.5.1: A CAPM Approach, GPFG

Excess fund returns, gross of costs, p-value of estimate shown in brackets

Note: Results for subsample 1 (2000-2007) do not change on exclusion of AA as GPFG did not invest in AA during this time frame.

	Simple CAPM Regression				Lagged CAPM Regression			
	2000-2007		2008-2017		2000-2007		2008-2017	
	Incl. AA	Excl. AA	Incl. AA	Excl. AA	Incl. AA	Excl. AA	Incl. AA	Excl. AA
$\hat{\alpha}_{GPFG}$	0.0093* (0.0490)	0.0093* (0.0490)	0.0076 (0.0513)	0.0067 (0.0796)	0.0090 (0.0522)	0.0090 (0.0522)	0.0076 (0.0539)	0.0067 (0.0800)
$\hat{\beta}_{m,0}$	0.4062** (0.0000)	0.4062** (0.0000)	0.6640** (0.0000)	0.6647** (0.0000)	0.4000** (0.0000)	0.4000** (0.0000)	0.6624** (0.0000)	0.6634** (0.0000)
$\hat{\beta}_{m,1}$					0.0881 (0.1760)	0.0881 (0.1760)	0.0060 (0.9106)	0.0048 (0.9291)
$\hat{\beta}_{m,0} + \hat{\beta}_{m,1}$					0.4881	0.4881	0.6684	0.6682
R ²	0.5324	0.5324	0.8197	0.8180	0.5602	0.5602	0.8197	0.8181

A benchmark approach

To reinforce our findings, we examined how fund returns mapped against returns of individual asset class benchmark indices. Not only did this extract implied asset allocations and determined if fund returns are consistent with reported allocations but also further decomposed funds’ exposure to asset class returns.

We employed Equation 4.1.6 (public equity and fixed income only) in a performance regression on GPFG’s 2000 – 2007 returns. Similarly, Equation 4.1.7 was used for GPFG’s 2008 – 2017 returns, as the fund began allocating to real estate in this period. Results can be seen in Table 6.5.2 and are very similar when excluding alternative assets, as expected given GPFG’s assets breakdown. Long exposure to public equity and fixed income indices explains GPFG returns well in both subsample periods with positive and significant $\beta_{GPFG, PubEq}$ and $\beta_{GPFG, FI}$ and R² of 0.79 and 0.87 for subsample 1 and 2, respectively. GPFG had short exposure to RE in 2008 – 2017, in line with their negative average real estate return.

In fulfilling the second objective of our Benchmark Approach to extract the implied versus reported asset allocations for the three funds, we undertook long-only style analysis to minimise the sum of squared residuals (SSR) with two restrictions: (1) $\sum \beta_{i,z} = 1$, and (2) $\beta_{i,z} \geq 0$. Using Equation 4.1.6 for 2000 – 2007,

GPFPG's results (40 percent public equity, 60 percent fixed income) were the same as reported, with significant $\beta_{GPFPG, PubEq}$ and $\beta_{GPFPG, FI}$. When we expanded the asset classes to include real estate in 2008 – 2017 (Equation 4.1.7), we noted $\beta_{GPFPG, RE}$ is zero (versus a reported 0.5 percent median allocation).

Table 6.5.2: A Benchmark Approach, GPFPG

Excess fund returns, gross of costs, p-value of estimate shown in brackets

Equation:	Performance Regression				Style Regression <i>Long-only restriction</i>	
	2000-2007		2008-2017		2000-2007	2008-2017
	Incl. AA <i>Eqn. 4.1.6</i>	Excl. AA <i>Eqn. 4.1.6</i>	Incl. AA <i>Eqn. 4.1.7</i>	Excl. AA <i>Eqn. 4.1.6</i>	Incl. AA <i>Eqn. 4.1.6</i>	Incl. AA <i>Eqn. 4.1.7</i>
$\hat{\alpha}_{GPFPG}$	0.0029 (0.2347)	0.0029 (0.2347)	0.0044 (0.1443)	0.0032 (0.2135)	0.0043 (0.1465)	0.0052 (0.1084)
$\hat{\beta}_{GPFPG, PubEq}$	0.4242** (0.0000)	0.4242** (0.0000)	0.6436** (0.0000)	0.6280** (0.0000)	0.3964** (0.0000)	0.6224** (0.0000)
$\hat{\beta}_{GPFPG, FI}$	0.7921** (0.0000)	0.7921** (0.0000)	0.5180** (0.0001)	0.5315** (0.0001)	0.6036** (0.0000)	0.3776** (0.0061)
$\hat{\beta}_{GPFPG, RE}$			-0.0147 (0.7443)			0.0000 (1.0000)
R ²	0.7905	0.7905	0.8719	0.8730	0.7741	0.8674

6.6 Future Fund (FF)

For FF, we noted again that only results from subsample 2 are available (Table 6.4.3). Upon examining [Appendix D](#), we saw that asset class weights evolved to be quite evenly split across public equity, fixed income and alternative assets, showing that alternative assets are a key component of FF's portfolio. Additionally, the very high Sharpe ratios exhibited by FF's alternative asset investments exceed Sharpe ratios of the comparable benchmark indices. The annualised Sharpe ratio for private equity is particularly high at 1.84, but we did note that this decreases markedly to 1.72 net of costs. It is also worthwhile noting that investments in public equity and fixed income result in less attractive Sharpe ratios, driven by high volatility.

Overall, FF outperforms its constructed benchmark with a Sharpe ratio of 0.54 vs. 0.44 respectively, and this can be attributed to the low overall standard deviation of returns (Figure 6.6.1). Quite notable is that the total fund standard deviation is equal to the lowest standard deviation amongst its asset classes, likely driven by low correlation between alternative asset returns and fixed income returns ([Appendix E](#)). Combined with the highly positive correlation displayed by FF

excess total returns with all component asset class benchmark indices ([Appendix C](#)), it appears FF management displays particular skill in diversification of returns.

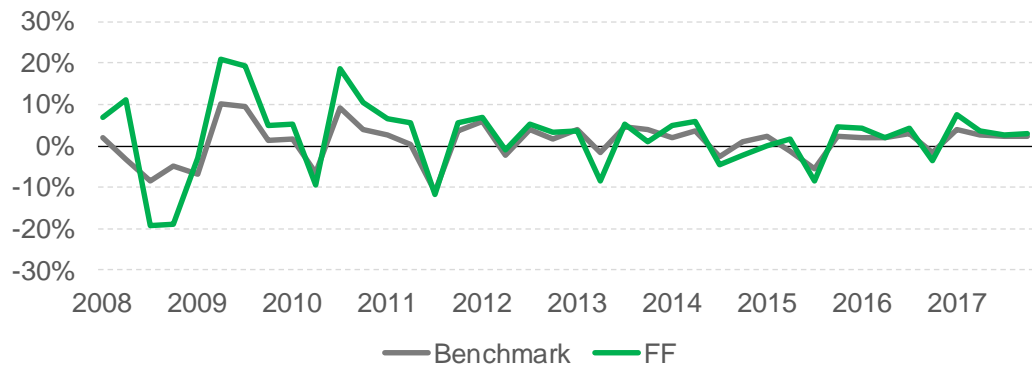


Figure 6.6.1 Future Fund vs. constructed benchmark excess quarterly returns

A CAPM approach

Table 6.6.1: A CAPM approach, FF

Excess fund returns, gross of costs, p-value of estimate shown in brackets

	Simple CAPM Regression		Lagged CAPM Regression	
	Incl. AA	Excl. AA	Incl. AA	Excl. AA
$\hat{\alpha}_{FF}$	0.0192** (0.0036)	0.0047 (0.2913)	0.0194** (0.0031)	0.0052 (0.2595)
$\hat{\beta}_{m,0}$	0.7826** (0.0000)	0.9498** (0.0000)	0.8099** (0.0000)	1.0122** (0.0000)
$\hat{\beta}_{m,1}$			-0.1023 (0.1982)	-0.2339** (0.0092)
$\hat{\beta}_{m,0} + \hat{\beta}_{m,1}$			0.7076	0.7783
R ²	0.7301	0.7340	0.7417	0.7752

Based on the simple CAPM results left (Table 6.6.1), we observed that FF has significant exposure to the market ($\beta_{m,0}$) and exhibits positive and significant alpha, in accordance with their active investment style. Nevertheless, we noted that compared to their median asset allocation to public

equities over subsample 2008 – 2017 (31 percent, Table 6.4.3), FF has the highest sensitivity to the excess market return ($\beta_{m,0}$). This is possibly due to the combination of FF returns’ high correlation with alternative asset indices (0.64 – 0.92) and the high correlation between the public equity and alternative asset class benchmark indices that we had chosen (0.73 – 0.95).

Upon removing alternative assets from FF’s portfolio, we identified that $\beta_{m,0}$ has increased. However, whilst the increase was not significant for GPFG, the market exposure for FF increased significantly, likely due to the loss of alternative assets’ diversification power for FF’s fixed income position ([Appendix E](#); and noted as key to their performance in [Section 6.4](#)) and the larger change in FF asset weights with the removal of alternative assets compared to GPFG (where alternative assets form a more minor component of the GPFG portfolio). Without alternative assets,

$\alpha_{FF}^{No\ Alt}$ falls significantly to the point where the FF does not appear to be generating alpha without alternative assets.

A benchmark approach

Similar to GPFG, we mapped FF returns against the return of asset class benchmark indices. Equation 4.1.8 was used for FF returns in the performance regression, and results can be seen in Table 6.6.2. Like GPFG, FF's returns are well explained by exposures to the indices chosen with R^2 of 0.85, though we noted that returns seem to be largely driven by exposure to fixed income and the hedge fund index (Other) and $\beta_{FF, PubEq}$ was oddly insignificant. Additionally, from visual inspection of the individual asset class returns mapped against our chosen benchmarks, we saw a large discrepancy for private equity returns for FF versus our private equity benchmark index (Section 5.2, Appendix F), which we assumed could be due to FF actively targeting a particular sector, style, size and/or strategy, or from the limitations of our selected private equity benchmark, which includes only publicly-listed private equity firms.

Given the lack of significant exposure to most alternative asset indices, we suspected that we may have chosen too many indices and thus had too many regressors included in our equation. To ameliorate this, we used Equation 4.1.9 and the constructed general alternatives index described in Section 5.2. Although the specification of alternatives to one (general) index did improve the individual explanatory power of some exposures, we noted that the overall explanatory power of this regression is slightly lower. In addition, we noted that α_{FF} was only significant gross of costs, but was still positive net of costs, so we could not reject the null hypothesis that $\alpha_{FF} \leq 0$ with 95 percent confidence. We next excluded alternative assets from FF returns and saw significant exposure ($\beta_{FF, PubEq}$ and $\beta_{FF, FI}$) from the performance regression, however the strong relationship to hedge fund returns (Other) remains. The move to significance for $\beta_{FF, PubEq}$ further evidenced our earlier finding that alternative assets have potentially strong diversifying power.

In a long-only style analysis of FF, returns are seen to be largely captured by the regressions (whether using Equation 4.1.8 or 4.1.9), reflected in the high R^2 . The discrepancy with the reported allocations stems from the style analysis' lower allocation to fixed income when compared to Table 6.4.3 asset weights, which is instead allocated to public equity, and infrastructure and timberland. Curiously,

there is no allocation to real estate or private equity, two components of FF’s reported portfolio of similar weight (2 percent each) to infrastructure and timberland (3 percent) (Table 6.4.3). In addition, $\beta_{FF,z}$ was insignificant for all asset classes z in the Equation 4.1.8 regression and only significant for $\beta_{FF, PubEq}$ in the Equation 4.1.9 regression.

Table 6.6.2: A Benchmark Approach, FF

Excess fund returns, gross of costs, p-value of estimate shown in brackets

Eqn:	Performance Regression				Style Regression <i>Long-only restriction</i>	
	Including Alternative Assets		Excluding Alternative Assets		Including Alternative Assets	
	Indiv. Indices <i>Eqn. 4.1.8</i>	GenAlt Index <i>Eqn. 4.1.9</i>	PubEq & FI <i>Eqn. 4.1.6</i>	Indiv. Indices <i>Eqn. 4.1.8</i>	Indiv. Indices <i>Eqn. 4.1.8</i>	GenAlt Index <i>Eqn. 4.1.9</i>
$\hat{\alpha}_{FF}$	0.0176** (0.0016)	0.0128* (0.0244)	0.0000 0.4999	0.0024 (0.3822)	0.0171** (0.0095)	0.0319** (0.0000)
$\hat{\beta}_{FF, PubEq}$	0.4350 (0.1397)	0.5247** (0.0037)	0.8999** 0.0000	0.9797* (0.0148)	0.4117 (0.2520)	0.5709** (0.0063)
$\hat{\beta}_{FF, FI}$	0.8413** (0.0025)	0.7815** (0.0002)	0.7227** 0.0063	1.0287** (0.0068)	0.2087 (0.5394)	0.2989 (0.2203)
$\hat{\beta}_{FF, RE}$	0.1717 (0.1345)			0.1592 (0.3092)	0.0000 (1.0000)	
$\hat{\beta}_{FF, PrivEq}$	-0.1721 (0.1849)			-0.1534 (0.3867)	0.0000 (1.0000)	
$\hat{\beta}_{FF, Infra}$	-0.1174 (0.6721)			-0.4827 (0.2022)	0.3277 (0.3328)	
$\hat{\beta}_{FF, Other}$	1.3203** (0.0006)			1.1203* (0.0320)	0.0519 (0.9116)	
$\hat{\beta}_{FF, GenAlt}$		0.2096 (0.2150)				0.1302 (0.5054)
R ²	0.8513	0.8060	0.7786	0.8110	0.7787	0.7406

6.7 Canada Pension Plan (CPP)

For CPP, we saw from the summary statistics (Tables 6.4.2 and 6.4.3) that asset allocations changed markedly from subsample 1 (2000 – 2007) to subsample 2 (2008 – 2017), with public equity falling from an 83 percent median allocation to 30 percent, while the median allocation to alternative assets increased from 7 percent to 39 percent. It should also be pointed out that CPPIB leverages its portfolio, and thus asset allocation weights sum to greater than 100 percent. Amongst the asset classes, we noted a substantial increase in Sharpe ratios from subsample 1 to subsample 2. Particularly notable is the annualised Sharpe ratio for

fixed income from 2008 - 2017, which is remarkably high (1.00 using gross returns) as its standard deviation is much lower than that of peers and the fixed income benchmark (Table 6.4.3). While Sharpe ratios increased in subsample 2, we also noted that this appears to have come at a cost. The Sharpe ratio in subsample 1 falls by 0.01 when including costs yet drops by 0.09 in subsample 2 when costs are included. The higher Sharpe ratios and costs may be attributed to the change in investment strategy to a more active approach.

Finally, we would like to highlight that upon applying the Lo adjustment, whilst quarterly Sharpe ratios for infrastructure and timberland and private equity appear high relative to other asset classes in CPP’s portfolio, on an annualised basis, they are much more in line with other CPP investments.

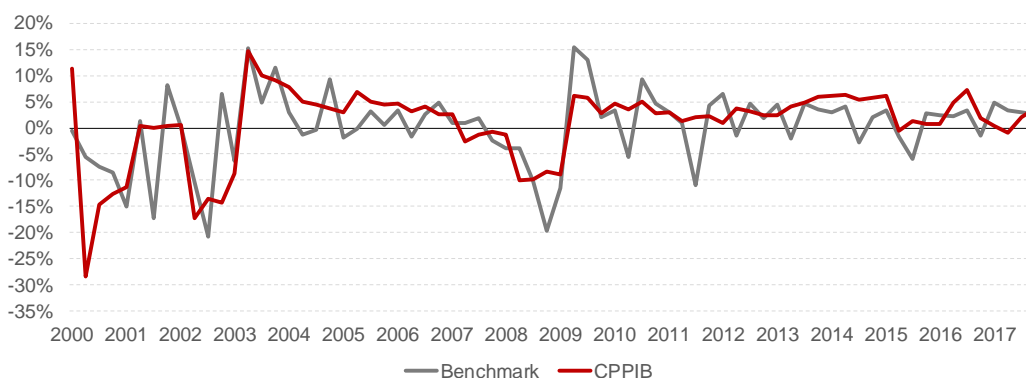


Figure 6.7.1 CPPIB vs. constructed benchmark excess quarterly returns

A CAPM approach

Based on the simple CAPM results below (Table 6.7.1), we observed that CPP has significant exposure to the market ($\beta_{m,0}$), as expected. We saw that CPP’s $\beta_{m,0}$ and α_{CPP} go through marked changes pre- and post-global financial crisis, with $\beta_{m,0}$ decreasing considerably and alpha moving from negative and insignificant to positive and significant.

Upon removing alternative assets, $\beta_{m,0}^{No Alt}$ (contrary to GPF and FF) decreased significantly, suggesting that the addition of alternative assets to CPP’s portfolio had added market exposure rather than diversifying power. $\alpha_{CPP}^{No Alt}$ in 2008 - 2017 decreased very slightly and remains positive and significant. However, we noted scepticism towards an interpretation of CPP’s alpha under the simple CAPM regression given potential remaining effects of stale pricing and/or manager-smoothed returns as discussed in Section 6.2, and thus extended our analysis for CPP.

Table 6.7.1: A CAPM Approach, CPP*Excess fund returns, gross of costs, p-value of estimate shown in brackets*

	Simple CAPM Regression				Lagged CAPM Regression			
	2000-2007		2008-2017		2000-2007		2008-2017	
	Incl. AA	Excl. AA	Incl. AA	Excl. AA	Incl. AA	Excl. AA	Incl. AA	Excl. AA
$\hat{\alpha}_{CPP}$	-0.0048 (0.3664)	-0.0060 (0.2773)	0.0184** (0.0006)	0.0163** (0.0000)	-0.0062 (0.3075)	-0.0070 (0.2182)	0.0181** (0.0003)	0.0162** (0.0000)
$\hat{\beta}_{m,0}$	0.6965** (0.0001)	0.5039** (0.0001)	0.2755** (0.0000)	0.1894** (0.0000)	0.6655** (0.0000)	0.4818** (0.0000)	0.2336** (0.0001)	0.1642** (0.0001)
$\hat{\beta}_{m,1}$					0.4414** (0.0024)	0.3141** (0.0030)	0.1570** (0.0079)	0.0945* (0.0291)
$\hat{\beta}_{m,0} + \hat{\beta}_{m,1}$					1.1068	0.7959	0.3906	0.2587
R ²	0.3519	0.3517	0.3473	0.3310	0.5085	0.5031	0.4517	0.4073

*An extended CAPM approach***CAPM with one lag on excess market returns**

Given that CPP returns still displayed serial correlation post-Lo adjustment, we proceeded with the AKL adjustment in an attempt to capture $\beta_{m,t}^{true}$ (Equation 4.3.1) by introducing a lagged excess market variable ($R_{m,t-1} - r_{f,t-1}$), as shown in Equation 4.2.1. The results can be seen above in Table 6.7.1.

$\beta_{m,1}$ is shown to be positive and significant for both subsamples. Thus, CPP's beta from the simple CAPM approach above understates CPP's market exposure. Accordingly, as $\beta_{m,1}$ is shown to provide a measure of explanatory power for CPP's returns (previously included in α_{CPP} under simple CAPM), we saw a slight decrease in α_{CPP} , but alpha remains significant in subsample 2. Upon removing alternative assets, we identified that CPP's contemporaneous and one-lag $\beta_{m,t}^{No Alt}$ are both significant, a result that was surprising and we revisit later. Meanwhile, $\alpha_{CPP}^{No Alt}$ remains positive and significant in subsample period 2008 - 2017.

Meanwhile, consistent with previous findings, we saw that one-lag $\beta_{m,1}$ for GPF and FF are both insignificant (Tables 6.5.1 and 6.6.1). The former is consistent with GPF's passive investment style and portfolio focus on public equity markets, whilst the latter indicates that despite the high allocation to alternative assets in their portfolio, FF does not appear to be experiencing stale pricing or smoothed returns.

CAPM with two lags on excess market returns

That CPP’s $\beta_{m,1}$ was positive and significant led us to continue with two lags on excess market returns (Appendix G), where we found that $\beta_{m,1}$ and $\beta_{m,2}$ are positive and significant for 2008 – 2017. Thus, CPP’s betas from previous CAPM regressions are again shown to understate true market exposure (here shown to be 0.50). Accordingly, we saw a slight decrease in α_{CPP} from 0.0181 to 0.0178 but remained positive and significant. However, in the subsample period 2000 – 2007, $\beta_{m,2}$ is now insignificant, indicating one lag is sufficient to capture CPP’s true market exposure in this subsample. Upon removing alternative assets, we identified that the lagged CPP betas are no longer significant (Appendix G), whilst CPP’s alpha without alternatives ($\alpha_{CPP}^{No\ Alt}$) puzzlingly remains positive and significant.

CAPM with three lags on excess market returns

That CPP’s $\beta_{m,1}$ and $\beta_{m,2}$ were both positive and significant leads us to continue three lags on excess market return for subsample 2 (Appendix G), where we saw that whilst $\beta_{m,1}$ remain positive and significant, $\beta_{m,2}$ and $\beta_{m,3}$ are positive but insignificant. It should be noted that the $\beta_{m,2}$ is only marginally insignificant (p-value 0.0602).

We were therefore satisfied that we had come to the appropriate number of lags k by which fund betas should be adjusted:

FF 2000 – 2007	Simple CAPM $\beta_{FF,m,0}$	n.a.
FF 2008 – 2017		0.7826
GPF 2000 – 2007	Simple CAPM $\beta_{GPF,m,0}$	0.4062
GPF 2008 – 2017		0.6640
CPP 2000 – 2007	CAPM with one-lag $\beta_{CPP,m,0} + \beta_{CPP,m,1}$	1.1068
CPP 2008 – 2017	CAPM with two-lags $\beta_{CPP,m,0} + \beta_{CPP,m,1} + \beta_{CPP,m,2}$	0.5005

These adjusted $\beta_{i,m}$ were then used in the computation of the funds’ Treynor ratios (Table 6.4.3), where we noted that for the level of systematic risk the funds take on, all three are outperforming the market in subsample 2008 – 2017.

An asymmetric CAPM approach

We were interested in delving deeper for CPP and exposing whether their observed serial correlation stemmed from stale pricing due to illiquidity or from intentionally managed pricing. Therefore, we proceeded to dissect lagged betas into ‘up market’ and ‘down market’ betas. If fund returns were driven by intentional managed

pricing, lagged betas in down markets would be more significant than for up markets (Section 4.2).

Asymmetric CAPM with one lag on excess market returns

Table 6.7.2: An asymmetric CAPM approach, CPP

Excess fund returns, gross of costs, p-value of estimate shown in brackets

	2000-2007	2008-2017
$\hat{\alpha}_{CPP}$	-0.0238* (0.1921)	0.0303** (0.0004)
$\hat{\beta}_{0,m}^{pos}$	0.8177* (0.0241)	0.2923* (0.0267)
$\hat{\beta}_{1,i}^{pos}$	0.6357* (0.0467)	-0.1007 (0.4259)
$\hat{\beta}_{0,i}^{neg}$	0.5447* (0.0492)	0.2338* (0.0129)
$\hat{\beta}_{1,m}^{neg}$	0.3514 (0.1693)	0.3155** (0.0010)
R ²	0.5182	0.5230

Results for CPP in the subsample 2000 – 2007 suggested that CPP’s serial correlation in this period is less due to intentional managed returns and more related to stale pricing, as illustrated by the insignificant $\beta_{m,1}^{neg}$ versus the significant $\beta_{m,1}^{pos}$ in Table 6.7.2. This picture remains the same when we removed alternative assets from CPP’s portfolio. In the subsample 2008 – 2017, we found significant $\beta_{m,1}^{neg}$ versus the insignificant $\beta_{m,1}^{pos}$, in line with what we would expect to see for managers more concerned about smoothing down-

market than up-market returns. It is interesting that this relationship between $\beta_{m,1}^{neg}$ and $\beta_{m,1}^{pos}$ persists even after we removed CPP’s alternative assets, indicating that opportunities to smooth returns do not only arise in the illiquid alternative asset classes. However, $\beta_{m,1}^{neg}$ decreased significantly from removing CPP’s alternative assets, reinforcing our hypothesis that funds have some scope to manage prices in illiquid assets.

Asymmetric CAPM with two lags on excess market returns

From Appendix H, we saw that in 2008 – 2017, $\beta_{m,1}^{neg}$ remains significant whilst $\beta_{m,1}^{pos}$ is insignificant. Meanwhile, although $\beta_{m,0}^{neg}$ and $\beta_{m,2}^{neg}$ are now insignificant, this is only marginally so and $\beta_{m,2}^{neg}$ still fulfils the criteria of being more significant than its positive counterpart. Thus, the results are largely uniform to findings in Section 6.5 and suggest that CPPIB manages their total returns two quarters back. After removing alternative assets, the decrease in $\beta_{m,1}^{neg}$ and $\beta_{m,2}^{neg}$ is again significant, but $\beta_{m,1}^{neg, No Alt}$ remains significant, again indicating that either CPPIB’s fixed income or public equity returns are contributing to this smoothed result.

Overall, we found indications that CPPIB have smoothed their alternative asset returns two quarters back in the period 2008 – 2017. However, given results from CPP’s asymmetric CAPM regression after removing alternative assets,

questions endure around the characteristics of CPP’s public equity and fixed income returns, a topic that will be explored further in the remainder of this section.

In addition, although not the primary focus of this analysis, it is noteworthy that GPFG in subsample 2000 – 2007 had significant $\beta_{m,1}^{neg}$ versus insignificant $\beta_{m,1}^{pos}$ (Appendix H). However, combined with GPFG’s lack of serial correlation (Sections 6.1 and 6.5) and the fact that 100 percent of their portfolio during this period is invested in public equity and fixed income markets, we believed this result is not of economic significance (and accepting the statistical significance would lead to a Type I error).

A factor approach

To fortify our analysis further and ensure that in our interpretation of α_{CPP} that we included the right risk factors, we expanded the number of risk factors using the four factors outlined in Section 3.2. We did note that the four factors are largely based on phenomena found in public equity but given alternative assets’ high correlation with the chosen public equity benchmark index (Appendix C), we assumed that the factors are still applicable to CPP (as well as GPFG and FF, for completeness).

Table 6.7.3: A Factor Approach
Excess fund returns, gross of costs, p-value of estimate shown in brackets

	GPFG		FF	CPP	
	2000-2007	2008-2017	2008-2017	2000-2007	2008-2017
$\hat{\alpha}_i$	-0.0017 (0.3978)	0.0076 (0.0527)	0.0181** (0.0060)	-0.0028 (0.4320)	0.0187** (0.0007)
$\hat{\beta}_{i,m}$	0.5667** (0.0000)	0.6265** (0.0000)	0.7550** (0.0000)	0.7402** (0.0007)	0.2794** (0.0000)
$\hat{\beta}_{i,HML}$	0.0648 (0.6588)	0.2585 (0.2704)	0.5308 (0.1404)	0.3078 (0.3917)	-0.0426 (0.8848)
$\hat{\beta}_{i,SMB}$	0.3113* (0.0103)	0.1237 (0.3689)	-0.0704 (0.7388)	-0.2467 (0.4065)	0.1081 (0.5311)
$\hat{\beta}_{i,UMD}$	0.1541* (0.0400)	-0.0359 (0.5661)	0.0015 (0.9875)	0.4028* (0.0284)	0.0369 (0.6377)
R ²	0.6419	0.8346	0.7501	0.5169	0.3595

Across both subsample periods, $\beta_{i,m}$ is positive and significant for all funds.

What is remarkable is the insignificant exposure to all risk factors except excess market return for all three funds in subsample 2 (2008 – 2017), possibly suggesting that they do not actively pursue factor investing. Furthermore, including these rewarded risk factors did not provide an explanation for CPP’s positive excess

return (α_{CPP}). Results are in line with earlier findings and we did not find it meaningful to pursue this line of inquiry further.

A benchmark approach

We have thus far been unable to disassemble CPP's performance, even when accounting for the true market exposure and including other compensatory risk factors. Thus, we took a benchmark approach to understand whether true source of α_{CPP} was more attributable to asset allocation or true active returns.

Performance regression

Equation 4.1.8 was used for CPP returns in the performance regression, and results can be seen in Table 6.7.4. We saw that exposure to the indices chosen only explains approximately half of the variation in CPP's returns. In addition, CPP still has positive and significant α_{CPP} , though this could be from the lack of explanatory power from the independent variables. Like FF, we saw a large discrepancy for CPP private equity returns versus our private equity benchmark index ([Section 5.2](#), [Appendix F](#)), possibly from CPP's active investment style or limitations of our benchmark.

Given the lack of significant exposure to all chosen indices, we again suspected that too many regressors had been included and used the general alternatives index ([Section 5.2](#)). Again, as for FF, the overall explanatory power of this regression is lower.

The lack of explanatory power in these performance regressions remained puzzling, so we excluded alternative assets from CPP's portfolio and re-examined the results. We wanted to determine if there were elements in CPP's public equity and fixed income returns that shared characteristics with the alternatives indices selected. Particularly, we were interested to see if the poor explanatory power in these regressions was from alternatives returns being incongruent with the alternatives indices, or that public equity and fixed income returns were incongruent with their benchmarks (as indicated may be the case from lagged and asymmetric CAPM regression results when we excluded alternative assets).

That explanatory power of benchmark indices remained insignificant across the board apart from $\beta_{CPP,PrivEq}$ in subsample 1 indicated that there is an element in either CPP's public equity or fixed income returns that appears to track the private equity index more than it track its own index. To follow-up, we used Equation 4.1.8 again, this time using CPP's public equity and fixed income excess

returns as dependent variables. These results can be found in [Appendix I](#) and indicate that CPP’s public equity strategy appears to offer private equity-like returns, and short exposure to the public equity benchmark.

Table 6.7.4: A Benchmark Approach – Performance Regression, CPP

Excess fund returns, gross of costs, p-value of estimate shown in brackets

	2000-2007				2008-2017			
	Including AA		Excluding AA		Including AA		Excluding AA	
	Indiv. Indices Eqn. 4.1.8	GenAlt Index Eqn. 4.1.9	PubEq & FI Eqn. 4.1.6	Indiv. Indices Eqn. 4.1.8	Indiv. Indices Eqn. 4.1.8	GenAlt Index Eqn. 4.1.9	PubEq & FI Eqn. 4.1.6	Indiv. Indices Eqn. 4.1.8
$\hat{\alpha}_{CPP}$	-0.0004 (0.4916)	-0.0016 (0.4623)	-0.0049 0.3223	-0.0033 (0.4133)	0.0158** (0.0022)	0.0147** (0.0041)	0.0154 0.0001	0.0140** (0.0001)
$\hat{\beta}_{CPP, PubEq}$	0.2517 (0.3997)	0.7414* (0.0192)	0.5009 0.0001	0.1657 (0.4418)	-0.4292 (0.1152)	-0.0878 (0.5713)	0.1795 0.0001	-0.2542 (0.1811)
$\hat{\beta}_{CPP, FI}$	0.3851 (0.5085)	-0.1786 (0.7308)	-0.1301 0.7140	0.2977 (0.4784)	0.3147 (0.2222)	0.2348 (0.1947)	0.1439 0.2849	0.3108 (0.0840)
$\hat{\beta}_{CPP, RE}$	-0.2077 (0.3914)			-0.1266 (0.4684)	-0.0532 (0.6160)			-0.0052 (0.9435)
$\hat{\beta}_{CPP, PrivEq}$	0.3808 (0.0560)			0.2816* (0.0500)	0.2341 (0.0513)			0.1558 (0.0629)
$\hat{\beta}_{CPP, Infra}$	0.0106 (0.9739)			-0.0061 (0.9792)	0.3286 (0.2001)			0.1272 (0.4773)
$\hat{\beta}_{CPP, Other}$	0.3417 (0.5945)			0.2838 (0.5397)	0.2496 (0.4808)			0.2210 (0.3708)
$\hat{\beta}_{CPP, GenAlt}$		-0.0807 (0.8495)				0.3568* (0.0140)		
R ²	0.4622	0.3567	0.3547	0.4665	0.5119	0.4509	0.3511	0.5209

Style analysis long-only

The pattern from the performance regression previously repeats for CPP, with insignificant $\beta_{CPP,z}$ in both subsample periods and R^2 of approximately 0.5. Setting aside the significance, we saw quite extraordinary implied asset weights for both subsamples in Table 6.8.4, especially in the 0 percent weight in public equities, 51 percent in fixed income and 38 percent in other (hedge funds) in 2008 – 2017. Referring again to [Appendix I](#), the first two are in line with finding of an insignificant $\alpha_{CPP PubEq}$ and positive and significant $\alpha_{CPP FI}$. That the allocation of public equity was not attributed to private equity exposure is more surprising, given our earlier finding that CPP’s public equity appears to offer private equity-like returns.

Using our constructed general alternatives index in lieu of the individual alternative benchmark indices, CPP’s implied versus reported asset allocations are

quite aligned in the 2000 – 2007 subsample. However, from 2008 – 2017, $\beta_{CPP, PubEq}$ is again 0, whilst the weight in fixed income (the only statistically significant exposure from both regressions) soars to 69 percent. We noted that R^2 is again lower with the general alternatives index compared to when all the alternative asset class benchmark indices are split out.

Table 6.7.5: A benchmark approach – Style analysis, CPP

Excess fund returns, gross of costs, p-value of estimate shown in brackets

Eqn:	Long-Only				Shorting Allowed			
	Indiv. Indices Eqn. 4.1.8		GenAlt Index Eqn. 4.1.9		Indiv. Indices Eqn. 4.1.8		GenAlt Index Eqn. 4.1.9	
	2000-2007	2008-2017	2000-2007	2008-2017	2000-2007	2008-2017	2000-2007	2008-2017
$\hat{\alpha}_{CPP}$	-0.0048 (0.4114)	0.0156** (0.0042)	-0.0066 (0.3509)	0.0116* (0.0303)	0.0008 0.4846	0.0156** (0.0026)	-0.0054 (0.3776)	0.0109* (0.0384)
$\hat{\beta}_{CPP, PubEq}$	0.2347 (0.4400)	0.0000 (1.0000)	0.7579* (0.0186)	0.0000 (1.0000)	0.2537 0.3966	-0.4497 (0.1041)	0.7996* (0.0130)	-0.1439 (0.3997)
$\hat{\beta}_{CPP, FI}$	0.1651 (0.7805)	0.5088 (0.0650)	0.2421 (0.6464)	0.6894** (0.0006)	0.3106 0.5943	0.4935 (0.0594)	0.2676 (0.6120)	0.7100** (0.0004)
$\hat{\beta}_{CPP, RE}$	0.0000 (1.0000)	0.0089 (0.9372)			-0.2080 0.3911	-0.0275 (0.7989)		
$\hat{\beta}_{CPP, PrivEq}$	0.3246 (0.1091)	0.1044 (0.4162)			0.3761 0.0593	0.2191 (0.0724)		
$\hat{\beta}_{CPP, Infra}$	0.0000 (1.0000)	0.0000 (1.0000)			0.0138 0.9661	0.2313 (0.3747)		
$\hat{\beta}_{CPP, Other}$	0.2757 (0.6728)	0.3778 (0.3183)			0.2538 0.6929	0.5333 (0.1380)		
$\hat{\beta}_{CPP, GenAlt}$			0.0000 (1.0000)	0.3106 (0.0544)			-0.0672 (0.8764)	0.4339** (0.0067)
R^2	0.4441	0.4417	0.3350	0.3203	0.4611	0.4966	0.3356	0.3336

Style analysis with shorting allowed

Particular to CPP is their ability to leverage their portfolio and take short positions. Therefore, we considered the possibility that the weaker fit between CPP returns and the regressions of Equation 4.1.8 and 4.1.9 were due to restriction (2) $\beta_{i,z} \geq 0$. We then removed this restriction to undertake returns attribution with shorting permitted. Given that CPP 2000 – 2007, GPF and FF results are quite similar to that of the long-only style analysis apart from small short positions taken in alternative assets (averaging -6 percent), the bulk of the remaining discussion will focus on CPP returns in subsample 2.

Mapped out against the individual asset class benchmarks, CPP’s returns match what we had come to think of as CPP investments that do not mimic the

broad characteristics of their respective asset classes. The sum of $\beta_{CPP,z}$ for private equity, infrastructure and timberland and other forms a staggering 98 percent of the portfolio, whilst a short position of 45 percent is taken in public equity. The general alternatives weight is much less extreme in the Equation 4.1.9 regression but is still accompanied by a short position of 14 percent in public equity.

6.8 Overall findings

We return to the premise of our paper, in which we sought to understand how the inclusion of alternative assets influences the risk-adjusted performance of long-term institutional portfolios as well as the impact of investment management style on the performance of alternative assets.

We suggest that given investing in alternative assets for GPFG is still in its nascency (less than 5 percent of the GPFG portfolio as of December 31, 2017) and that the strength of their returns is mostly driven by publicly-listed equity and fixed income investments, they can potentially derive valuable lessons from the FF and CPP management of alternative assets. We therefore related the bulk of our findings to FF and CPP, comparing (1) CPP's development from pre- to post-global financial crisis and (2) FF and CPP in the post-crisis period of 2008 – 2017.

After CPPIB changed to an active investment approach in subsample 2, we saw that their α_{CPP} thereafter turned positive and significant, indicating a positive influence from a greater focus on alternative assets. Nonetheless, when comparing CPP and FF in 2008 – 2017, we faced difficulties in separating out the 'true' α_{CPP} arising from CPPIB management skill and relating this to their investment in alternative assets. CPP's investments in public equity during this period did not mimic the broad characteristics of the asset class and instead took on the traits of private equity ([Appendix I](#)). This is likely due to their ability to leverage their portfolio and take short positions, and their investment strategy's focus on a matrix of geographic and sector exposures rather than asset class allocations ([Section 2.3](#))¹. Given the low R^2 from our regressions, we were ultimately unable to fully disassemble CPP's performance even after accounting for their 'true' market exposure and including other compensatory risk factors. Thus while α_{CPP} is positive and statistically significant, we suggest that it could also be due to the lack

¹ Additionally, CPPIB had a unit in its public market investments department which was dedicated to global tactical asset allocation. The unit was wound down in November 2016 but likely has contributed to the fund's public equity returns mimicking that of private equity.

of explanatory power from the independent variables. In addition, the strong α_{CPP} appears to persist even after removing alternative assets from CPP's portfolio (although the decrease from α_{CPP}^{All} to $\alpha_{CPP}^{No Alt}$ is statistically significant). This leaves us to propose that whilst alternative assets appear to have a positive and statistically significant impact on CPP's portfolio since their move to active investing, we were unable to conclude so with any definiteness.

A note of caution can also be gleaned from the observation of intentional smoothing of returns by CPPIB in subsample 2. CPPIB's focus on investing in illiquid and private assets combined with internal investment management (Section 2.3) creates potential for a misalignment in incentives. We propose that when both management and returns evaluation are accountable to the same group, alternative assets provide scope for managing returns such that the portfolio appears more attractive on a risk-return basis over time across various forms of performance measurements.

FF forms an interesting and useful counterpart to CPP in our analysis, demonstrating that alternative assets can also be an effective tool to diversify portfolio risk and generate positive and significant α_{FF} both gross and net of costs. The R^2 for FF regressions have also been much higher at around 75 to 85 percent, and $\alpha_{FF}^{No Alt}$ is still positive but no longer significant. We therefore believe that the inclusion of alternative assets in FF's portfolio has been very favourable to their risk-adjusted performance, as evidenced by low correlation with its fixed income investments (Appendix E). It is remarkable that whilst CPP and FF both invest heavily in alternative assets, FF is not observed to exhibit manager-smoothed returns. We propose this is linked to their external investment management (Section 2.4), whereby they face stronger incentives to push for accurate and timely disclosure from their external managers to aid in regular evaluation of managers on such metrics.

Similar to CPPIB, NBIM manages most of the GPFG portfolio internally. As their AUM grows, GPFG could consider increasing their allocation to alternative assets to utilise potential diversification benefits as observed in FF (Appendix E). However, it is important to note that alternative asset benchmarks do not display negative correlation with other asset class benchmarks and thus we believe it is necessary to have skilled active managers to unlock the diversification powers of alternative assets. This approach may be of lesser interest to GPFG as their strategy focuses on beta returns.

Given the scope alternative assets can provide in allowing managers to smooth returns (as shown in CPP results) and considering GPFG's focus on internal management, we are hesitant to recommend that alternative assets remain in-house. With thought to GPFG's fiduciary duty to the government and people of Norway, we would instead suggest external managers of alternative assets as a feasible path to accessing the potential benefits of alternative assets whilst keeping incentives aligned but note the opposing force of potential agency problems.

Limitations

The results of our analysis combined with the economic intuition of the investment models under review provide a strong basis for interpretation of our results. However, our results are limited in some respects, detailed further below.

We begin by noting that GPFG, CPPIB and FF do not provide data on re-allocation of AUM between asset classes and re-investment ratios of distributions. We acknowledge that without this data, part of the per asset class returns could be mis-attributed to performance, especially as the funds dynamically manage asset allocations and re-investment does not necessarily occur in the same allocation ratio. As noted in [Section 5.1](#), the assumptions made to normalise each fund's returns, costs and transfers of capital could affect returns, particularly considering that CPPIB investment income per asset class is only available on an annual basis.

The lack of liquid and available benchmarks for alternative assets across the entire time frames may limit some results, particularly return attribution and style analysis. Although we do construct benchmarks to match the alternative asset classes (detailed in [Section 5.2](#)), there remains the possibility that the benchmarks are not properly reflective of the alternative asset investments held by the funds. This is particularly relevant to our PE benchmark (LPX Composite), as the characteristics of publicly-listed private equity companies may not be fully representative of the private equity fund universe available to FF and CPP, and the performance of listed PE firms may not reflect the returns to the PE universe as a whole. We also note that the style analysis provides a static measure and may provide poor explanation of returns when asset class allocations change dramatically or quickly within the subsample periods.

Finally, our estimation of the performance of the funds without alternative assets has a few implicit assumptions that limit the interpretation of these results. Firstly, when removing alternative asset investments, we make an implicit assumption that these funds are instead reapportioned to public equities and fixed income in the relative proportions as when alternatives were included in the portfolio ([Section 4.4](#)). However, as noted in [Section 6.3](#), alternative assets generally have a very high correlation with public equities, and thus if barred from investing in alternative assets, GPFG, CPP and FF may have allocated a larger relative proportion of investments to public equities. We note that this implicit assumption is particularly impactful for FF and CPP, which have substantial

allocations to alternatives. GPFG's small allocation to real estate limits the impact of this assumption on interpretation of GPFG results.

In addition, when removing alternative assets from the funds, we implicitly assumed that the capital reapportioned to public equity and fixed income achieves the same returns at the same level of fees. We note that it is unlikely, given the large allocation to alternatives in CPP and FF, that the same returns could be achieved without an increase in relative costs. Using elements from Berk & Green's (2004) model of mutual fund flows, it is reasonable to believe that with more capital allocated to an asset class, it would become harder to find similarly attractive investments, and would likely require a larger relative team. While the assumption of scalable returns is likely not a reasonable one, we note that this assumption has not affected our results for FF, where fund returns excluding alternative assets did not generate excess returns beyond what could be explained by exposure to risk. It weakens our findings that CPP still has significant α_{CPP} without alternative assets, but we remain sceptical of that finding due to the presence of smoothed returns.

Conclusion

The aim of this paper has been to understand how the inclusion of alternative assets influences risk-adjusted performance of long-term institutional portfolios and the impact of investment management style. To answer this, we used Norway's GPF, Canada's CPP and Australia's FF returns in the context of their investment models with a focus on alternative assets to determine if better risk-adjusted performance can be attributed to the use of alternatives in a long-term portfolio.

After adjusting returns for serial correlation, we decomposed fund returns into manager skill (alpha) and exposure to (1) the market and other compensated factors, or (2) benchmark indices. We found FF and GPF returns well-explained from exposure to relevant benchmarks and consistent with their respective investment models. FF generates a positive and significant alpha, while GPF does not, in line with their respective focus on alpha- (active) and beta- (passive) driven returns. CPP's performance remains an enigma, as we were unable to disassemble CPP's returns even accounting for their 'true' market exposure using lagged betas. This may be attributed to their ability to leverage their portfolio and take short positions, and their matrix-style benchmark portfolio.

To distinguish the role of alternative assets, we re-examined our results, this time excluding alternative assets from fund holdings. Doing so for GPF does not markedly change performance, which is unsurprising given limited focus in this area. FF's positive and significant alpha disappears when alternative assets are removed, and thus we believe that active exposure to alternative assets can improve risk-adjusted performance when deployed effectively. Exclusion of alternative assets from CPP resulted in decreased, but still positive and significant, alpha.

We caution that despite the benefits, the illiquid and opaque nature of alternative assets can also provide scope for manager-smoothed returns, as seen in CPP after they moved to an active investment style in 2006. We argue that CPP's focus on investing in illiquid and private assets combined with their internal investment management style creates potential for a misalignment in incentives.

Overall, we believe alternative assets can be the right tool in the right hands, offering both potential diversification benefits to a portfolio, but also the capacity to smooth portfolio returns artificially. Inclusion of alternative assets in a long-term institutional portfolio should be approached with a healthy degree of scepticism, particularly when management and reporting of the assets is performed by the same group (as in internal investment management).

Bibliography

- Ambachtsheer, K. P. (2016). Norway versus Yale - or versus Canada?: A Comparison of Investment Models. *The Future of Pension Management* (pp. 133-139). Hoboken, NJ: John Wiley & Sons, Incorporated.
- Ang, A., Brandt, M. W., & Denison, D. F. (2014). Review of the active management of the Norwegian Government Pension Fund Global. *External Report to the Norwegian Ministry of Finance*.
- Asness, C. S. (1995). The power of past stock returns to explain future stock returns. [dx.doi.org/10.2139/ssrn.2865769](https://doi.org/10.2139/ssrn.2865769)
- Asness, C., Krail, R., & Liew, J. (2001). Do Hedge Funds Hedge? *Journal of Portfolio Management*, 28, 1.
- Australian Government. (2006). Future Fund Act 2006. Retrieved from www.legislation.gov.au/Details/C2012C00178
- Australian Government. (2017). Future Fund investment mandate direction 2017. Retrieved from www.legislation.gov.au/Details/F2017L00597
- Ballard, E. (2017, April 7). Norway's Giant Sovereign-Wealth Fund May Invest in Private Equity. *The Wall Street Journal*. Retrieved from www.wsj.com
- Berk, J. B., & Green, R. C. (2004). Mutual fund flows and performance in rational markets. *Journal of political economy*, 112(6), 1269-1295.
- Bird, R., Liem, H., & Thorp, S. (2013). The Tortoise and the Hare: Risk Premium versus Alternative Asset Portfolios. *Journal of Portfolio Management*, 39(3), 112-122,114. doi:10.3905/jpm.2013.39.3.112
- Black, F., Jensen, M.C, & Scholes, M.C. (1972). The capital asset pricing model: Some empirical tests. In M.C. Jensen (Ed.), *Studies in the theory of capital markets* (pp. 79–124). New York: Praeger
- Black, F., & Litterman, R. (1992). Global portfolio optimization. *Financial Analysts Journal*, 48(5), 28-43.
- Blundell-Wignall, A., Hu, Y.-W., & Yermo, J. (2008). Sovereign wealth & pension fund issues. *OECD Journal: Financial Market Trends*, 2008(1), 117. doi:10.1787/fmt-v2008-art5-en
- Bodie, Z., & Brière, M. (2013). Sovereign wealth and risk management: a framework for optimal asset allocation of sovereign wealth.
- Bodie, Z., Kane, A., & Marcus, A. J. (2014). *Investments, 10e*. McGraw-Hill Education.

- Boubakri, N., Cosset, J.-C., & Grira, J. (2016). Sovereign wealth funds targets selection: A comparison with pension funds. *Journal of International Financial Markets, Institutions & Money*, 42, 60-76.
doi:10.1016/j.intfin.2016.01.004
- Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1), 57-82.
- CEM Benchmarking. (2017). Asset allocation and fund performance of defined benefit pension funds in the United States, 1998 – 2015 (updated). Retrieved from www.cembenchmarking.com/Files/Documents/Research/Asset_Allocation_and_Fund_Performance_Executive_Summary_Update_2017.pdf
- Chambers, D., Dimson, E., & Imanen, A. (2012). The Norway Model. *Journal of Portfolio Management*, 38(2), 67-81, 68.
- CPPIB. (2018a). A total portfolio view. Retrieved from www.cppib.com/en/how-we-invest/our-investment-strategy/a-total-portfolio-view/
- CPPIB. (2018b). Active management. Retrieved from www.cppib.com/en/how-we-invest/our-investment-strategy/active-management/
- CPPIB. (2018c). Investment framework. Retrieved from www.cppib.com/en/how-we-invest/our-investment-strategy/investment-framework/
- CPPIB. (2018d). Our story. Retrieved from www.cppib.com/en/who-we-are/our-story/
- CPPIB. (2018e). What we do. Retrieved from www.cppib.com/en/what-we-do/
- Croce, R. D., Stewart, F., & Yermo, J. (2011). Promoting longer-term investment by institutional investors. *OECD Journal: Financial Market Trends*, 2011(1), 145-164.
- Cumming, D., Haß, L. H., & Schweizer, D. (2014). Strategic Asset Allocation and the Role of Alternative Investments. *European Financial Management*, 20(3), 521-547
- DeBondt, W. F., & Thaler, R. (1985). Does the stock market overreact?. *The Journal of Finance*, 40(3), 793-805.
- Doeswijk, R., Lam, T., & Swinkels, L. (2014). The global multi-asset market portfolio, 1959–2012. *Financial Analysts Journal*, 70(2), 26-41.
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3-56.

- Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, 51(1), 55-84.
- Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 105(3), 457-472.
- FF. (2013). Long term investing. Retrieved from www.futurefund.gov.au/investment/how-we-invest/investment-policy-and-position-papers
- FF. (2017). 2016-2017 annual report. Retrieved from www.futurefund.gov.au/about-us/annual-reports
- FF. (2018a). About us. Retrieved from www.futurefund.gov.au/about-us/faqs
- FF. (2018b). Investment beliefs. Retrieved from www.futurefund.gov.au/investment/how-we-invest/investment-beliefs
- FF. (2018c). Portfolio update at 31 March 2018. Retrieved from www.futurefund.gov.au/investment/investment-performance/portfolio-updates
- FF. (2018d). Statement of investment policies. Retrieved from www.futurefund.gov.au/investment/how-we-invest/investment-policy-and-position-papers
- Fotak, V., Gao, X., & Megginson, W. L.. (2017). A financial force to be reckoned with?: An overview of sovereign wealth funds. In *The Oxford Handbook of Sovereign Wealth Funds.*: Oxford University Press.
doi:10.1093/oxfordhb/9780198754800.013.1
- Fouche, G. (2017, November 16). Norway's \$1 trillion wealth fund proposes to drop oil, gas stocks from index. *Reuters*. Retrieved from www.reuters.com
- French, K.R. (n.d.). Data Library. Retrieved from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
- Getmansky, M., Lo, A. W., & Makarov, I. (2004). An econometric model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial Economics*, 74(3), 529-609.
- Golec, J. H. (1996). The effects of mutual fund managers' characteristics on their portfolio performance, risk and fees. *Financial Services Review*, 5(2), 133-147.
- Government of Canada. (2016). Contributions to the Canada Pension Plan.
Retrieved from

www.canada.ca/en/services/benefits/publicpensions/cpp/contributions.htm
1

- Government of Canada. (2017). Canadian Pension Plan enhancement. Retrieved from www.canada.ca/en/services/benefits/publicpensions/cpp/cpp-enhancement.html
- He, G., & Litterman, R. (1999). The intuition behind Black-Litterman model portfolios.
- Hudson. (2015). Norway vs Yale vs Canada: Weighing Up Investment Models for the Long Term. *BNY Mellon*. Retrieved from www.bnymellon.com/_global-assets/pdf/foresight/norway-vs-yale-vs-canada-weighing-up-investment-models-for-the-long-term.pdf
- Ibbotson, R. G., & Kaplan, P. D. (2000). Does asset allocation policy explain 40, 90, or 100 percent of performance?. *Financial Analysts Journal*, 56(1), 26-33.
- IMF. (2015). Global Financial Stability Report. Retrieved from www.imf.org/en/Publications/GFSR/Issues/2016/12/31/Global-Financial-Stability-Report-April-2015-Navigating-Monetary-Policy-Challenges-and-42422
- Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1), 65-91.
- Jensen, M. C. (1968). The performance of mutual funds in the period 1945–1964. *The Journal of finance*, 23(2), 389-416.
- Lee, W. (2000). Theory and methodology of tactical asset allocation (Vol. 65). John Wiley & Sons.
- Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics*, 222-224.
- Litterman, R. (2003). *Modern investment management: An equilibrium approach* (Wiley finance series). Hoboken, N.J: Wiley.
- Liu, Y., Sun, S., Huang, R., Tang, T., & Wu, X. (2017). The Rise of Alternative Assets and Long-Term Investing. *The Boston Consulting Group*. Retrieved from http://image-src.bcg.com/Images/BCG_Rise-of-Alternative-Assets-Long-Term-Investing_ENG_Mar2017_tcm72-153959.pdf

- Lo, A. W. (2002). The statistics of Sharpe ratios. *Financial analysts journal*, 58(4), 36-52.
- Lo, A. W. (2008). Hedge Funds: An Analytic Perspective. *Economics Books*.
- Louch, W. (2017, March 17). Blackstone collects \$5bn for first longer-life fund. *Financial News*. Retrieved from <https://www.fnlondon.com>
- Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, 7(1), 77-91. doi:10.2307/2975974
- Marlowe, J. (2014). Socially Responsible Investing and Public Pension Fund Performance. *Public Performance & Management Review*, 38(2), 337-358.
- Marriage, M. (2015, February 8). Pension pay dilemma becomes acute. *Financial Times*. Retrieved from www.ft.com
- Martinez-Oviedo, R., & Medda, F. (2017). Assessing the effects of adding timberland and farmland into resource-based Sovereign Wealth Fund portfolios. *Journal of Economics and Business*, 91, 24-40.
- McCahery, J. A., & de Roode, F. A. (2017). Co-investments of sovereign wealth funds in private equity. In *The Oxford Handbook of Sovereign Wealth Funds*.: Oxford University Press. doi:10.1093/oxfordhb/9780198754800.013.5
- Meggison, W. L., & Fotak, V. (2015). Rise of the fiduciary state: A survey of sovereign wealth fund research. *Journal of Economic Surveys*, 29(4), 733-778. doi:10.1111/joes.12125
- Ministry of Finance. (2017). Strategic benchmark index. *Government of Norway*. Retrieved from www.regjeringen.no/en/topics/the-economy/the-government-pension-fund/government-pension-fund-global-gpfg/strategic-benchmark-index-for-the-govern/id696850/
- NBIM. (2017a). About us. Retrieved from www.nbim.no/en/organisation/about-us/
- NBIM. (2017b). Benchmarks. Retrieved from www.nbim.no/en/investments/benchmark-indices/
- NBIM. (2017c). Risk management. Retrieved from www.nbim.no/en/investments/investment-risk/
- NBIM. (2018a). The fund. Retrieved from www.nbim.no/en/the-fund/
- NBIM. (2018b). The history. Retrieved from www.nbim.no/en/the-fund/the-history/

- Papaioannou, M. G., & Rentsendorj, B. (2015). Sovereign Wealth Fund Asset Allocations—Some Stylized Facts on the Norway Pension Fund Global. *Procedia Economics and Finance*, 29, 195-199.
- Preqin. (2018). 2018 Sovereign Wealth Fund Review. Retrieved from <http://docs.preqin.com/samples/The-2018-Preqin-Sovereign-Wealth-Fund-Review-Sample-Pages.pdf>
- Roumeliotis, G. (2014, November 18). Blackstone chases Buffett with 'core' private equity. *Reuters*. Retrieved from www.reuters.com
- Rozaanov, A. (2015). Public Pension Fund Management: Best Practice and International Experience. *Asian Economic Policy Review*, 10(2), 275-295. doi:10.1111/aepr.12106
- Rozaanov, A. (2017). Public Sector Investment Funds: How the Best-in-Breed Evolved. *Columbia University Program on Public Pension and Sovereign Funds, Working Paper No, 1*.
- Satchell, S. (2011). Forecasting expected returns in the financial markets. Academic Press.
- Sarney, M., & Preneta, A. M. (2001). The Canada Pension Plan's Experience With Investing Its Portfolio in Equities. *Social Security Bulletin*, 64, 46.
- Scholz, H., & Wilkens, M. (2005). A jigsaw puzzle of basic risk-adjusted performance measures. *The Journal of Performance Measurement*, 9(3), 57-64.
- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, 19(3), 425-442.
- Sharpe, W. F. (1966). Mutual fund performance. *The Journal of business*, 39(1), 119-138.
- Sharpe, W. F. (1992). Asset allocation: Management style and performance measurement. *Journal of portfolio Management*, 18(2), 7-19.
- Sharpe, W. F., & Tint, L. G. (1990). Liabilities—A new approach. *The Journal of Portfolio Management*, 16(2), 5-10.
- Terhaar, K., Staub, R., & Singer, B. (2003). Appropriate policy allocation for alternative investments. *Journal of Portfolio Management*, 29(3), 101-110.
- Thompson, J. (2017, September 24). Canada's trailblazing pension reforms pay dividends. *Financial Times*. Retrieved from www.ft.com/
- Towner, M. (2014). Norway's summit on responsible investing. *Journal of Investment Management*, 12(01), 33-44.

- Treynor, J. L. (1965). How to rate management of investment funds. *Harvard business review*, 43(1), 63-75.
- World Bank. (2017). *The evolution of the Canadian pension model : practical lessons for building world-class pension organizations (English)*. Washington, D.C. : World Bank Group.
- Xu, X. (2017). The Australian Future Fund. In *The Oxford Handbook of Sovereign Wealth Funds*.: Oxford University Press.
doi:10.1093/oxfordhb/9780198754800.013.15

Appendix A: Volatility Ratios

Table A.1: Ratio of annual volatility to annualised quarterly volatility

Volatility Ratios	2000-2017	2000-2007	2008-2017
	<i>Full period</i>	<i>Subsample 1</i>	<i>Subsample 2</i>
Future Fund			
Public equity	1.07		1.07
Fixed income	0.72		0.72
Alternative assets			
Private equity	1.55		1.55
Infrastructure & timberland	1.33		1.33
Property & real estate	1.21		1.21
Other	1.40		1.40
Total alternatives	1.33		1.33
Total FF return	0.97	n.a.	0.97
CPP			
Public equity	1.43	1.51	1.39
Fixed income	0.95	0.85	1.25
Alternative assets			
Private equity	1.75	1.71	1.80
Infrastructure & timberland	1.62	1.25	1.69
Property & real estate	1.50	1.37	1.86
Other	1.29	1.32	1.32
Total alternatives	1.67	1.57	1.81
Total CPP return	1.47	1.46	1.60
GPFG			
Public equity	1.28	1.30	1.26
Fixed income	1.18	0.86	1.16
Alternative assets			
Private equity			
Infrastructure & timberland			
Property & real estate	0.52		0.13
Other			
Total alternatives	0.52		0.13
Total GPFG return	1.15	0.92	0.25

Table A.2: Results of serial correlation regression, total fund returns

Serial correlation of returns

Excess fund returns, gross of costs, p-value of estimate shown in brackets

	FF		CPP		GPEG	
	2000-2007	2008-2017	2000-2007	2008-2017	2000-2007	2008-2017
$\hat{\alpha}$	<i>n.a.</i>	0.0183	-0.0064	0.0069*	0.0087	0.0089
	<i>n.a.</i>	(0.1008)	(0.2829)	(0.0356)	(0.1563)	(0.2047)
s.e.($\hat{\alpha}$)	<i>n.a.</i>	0.0143	0.0111	0.0038	0.0086	0.0108
$\hat{\beta} = \rho$	<i>n.a.</i>	0.1670	0.4692**	0.6581**	0.0058	0.2229
	<i>n.a.</i>	(0.3009)	(0.0031)	(0.0000)	(0.9750)	(0.1587)
s.e.($\hat{\beta}$)	<i>n.a.</i>	0.1615	0.1584	0.1157	0.1859	0.1581

Table A.3: Results of serial correlation regression, CPP asset class returns

Subsample 1: 2000-2007

Excess fund returns, gross of costs, p-value of estimate shown in brackets

	Public Eq.	Fixed Inc.	Private Eq.	Infra. & timber	Real estate	Other alt.⁽¹⁾
$\hat{\alpha}$	-0.0046	-0.0007	0.0057	0.0064	0.0137	<i>n.a.</i>
	(0.695)	(0.749)	(0.384)	(0.452)	(0.424)	<i>n.a.</i>
s.e.($\hat{\alpha}$)	0.0115	0.0021	0.0065	0.0083	0.0167	<i>n.a.</i>
$\hat{\beta} = \rho$.5205**	0.04877	0.7646**	0.4115	0.5380**	<i>n.a.</i>
	(0.002)	(0.171)	(0.000)	(0.135)	(0.000)	<i>n.a.</i>
s.e.($\hat{\beta}$)	0.1545	0.0345	0.1349	0.2582	0.0914	<i>n.a.</i>

(1) Other alternatives do not have enough data for meaningful estimation in subsample 1

Subsample 2: 2008-2017

Excess fund returns, gross of costs, p-value of estimate shown in brackets

	Public Eq.	Fixed Inc.	Private Eq.	Infra. & timber	Real estate	Other alt.
$\hat{\alpha}$	0.0080	0.0070	0.0060	0.0049	0.0030	-0.0005
	(0.319)	(0.078)	(0.187)	(0.105)	(0.271)	(0.489)
s.e.($\hat{\alpha}$)	0.0079	0.0039	0.0045	0.0030	0.0027	0.0007
$\hat{\beta} = \rho$	0.5805**	0.4391**	0.8209**	0.7808**	0.8572**	0.4348**
	(0.0000)	(0.005)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
s.e.($\hat{\beta}$)	0.1304	0.1474	0.0928	0.1007	0.08252	0.0891

Appendix B: Serial Correlation, Post-Lo Adjustment

Table B.1: Results of serial correlation regression, CPP all assets (All) and CPP excluding alternative assets (No Alt.) after Lo adjustment

<u>Subsample 1: 2000-2007</u> <i>Excess fund returns, gross of costs, p-value of estimate shown in brackets</i>	<u>CPP</u> <i>All</i>	<u>CPP</u> <i>No Alt.</i>
$\hat{\alpha}$	-0.0074 <i>(0.3135)</i>	-0.0069 <i>(0.2696)</i>
s.e.($\hat{\alpha}$)	0.0153	0.0112
$\hat{\beta} = \rho$	0.4692** <i>(0.0031)</i>	0.4628** <i>(0.0036)</i>
s.e.($\hat{\beta}$)	0.1584	0.1590

<u>Subsample 2: 2008-2017</u> <i>Excess fund returns, gross of costs, p-value of estimate shown in brackets</i>	<u>CPP</u> <i>All</i>	<u>CPP</u> <i>No Alt.</i>
$\hat{\alpha}$	0.00659 <i>(0.1045)</i>	0.0078 <i>(0.0408)</i>
s.e.($\hat{\alpha}$)	0.0055	0.0045
$\hat{\beta} = \rho$	0.6902** <i>(0.0000)</i>	0.5845** <i>(0.0000)</i>
s.e.($\hat{\beta}$)	0.1169	0.1301

Appendix C: Correlation of Indices

Table C.1: Correlations between indices and total fund returns before costs

Subsample 1: 2000-2007

	Public equity	Fixed income	Private equity	Infra. & timber	Property & real estate	Other alternatives	Real assets index	General alternatives	Australia	Canada	Norway
Public equity	1.0000	-0.0637	0.7824	0.4455	0.4670	0.2694	0.6815	0.8125	n.a.	0.5932	0.7296
Fixed income		1.0000	-0.3446	0.0513	0.1137	0.0513	0.3492	0.1114	n.a.	-0.1004	0.4606
Private equity			1.0000	0.4306	0.4659	0.3262	0.4701	0.7592	n.a.	0.6394	0.4369
Infra. & timber				1.0000	0.4761	0.4272	0.4750	0.5269	n.a.	0.3089	0.4181
Property & real estate					1.0000	0.1846	0.7760	0.7820	n.a.	0.2324	0.5185
Other alternatives						1.0000	0.1518	0.2655	n.a.	0.3071	0.2640
Real assets index							1.0000	0.9280	n.a.	0.2719	0.7997
General alternatives								1.0000	n.a.	0.4557	0.7652
Australia									n.a.	n.a.	n.a.
Canada										1.0000	0.4447
Norway											1.0000

Subsample 2: 2008-2017

	Public equity	Fixed income	Private equity	Infra. & timber	Property & real estate	Other alternatives	Real assets index	General alternatives	Australia	Canada	Norway
Public equity	1.0000	0.2083	0.8559	0.9475	0.7301	0.8835	0.9099	0.9234	0.8545	0.5893	0.9053
Fixed income		1.0000	-0.0484	0.3923	0.1929	0.0168	0.4056	0.1248	0.4322	0.2277	0.4113
Private equity			1.0000	0.7748	0.8547	0.8073	0.7933	0.9706	0.6708	0.6362	0.7242
Infra. & timber				1.0000	0.7513	0.8003	0.9386	0.8800	0.8625	0.6219	0.9048
Property & real estate					1.0000	0.5731	0.7720	0.8644	0.6365	0.5885	0.6572
Other alternatives						1.0000	0.8502	0.8695	0.8012	0.5623	0.7769
Real assets index							1.0000	0.9163	0.9209	0.5912	0.8745
General alternatives								1.0000	0.8055	0.6514	0.8216
Australia									1.0000	0.3825	0.8301
Canada										1.0000	0.5351
Norway											1.0000

Appendix D: Asset Class Weights Over Time by Fund

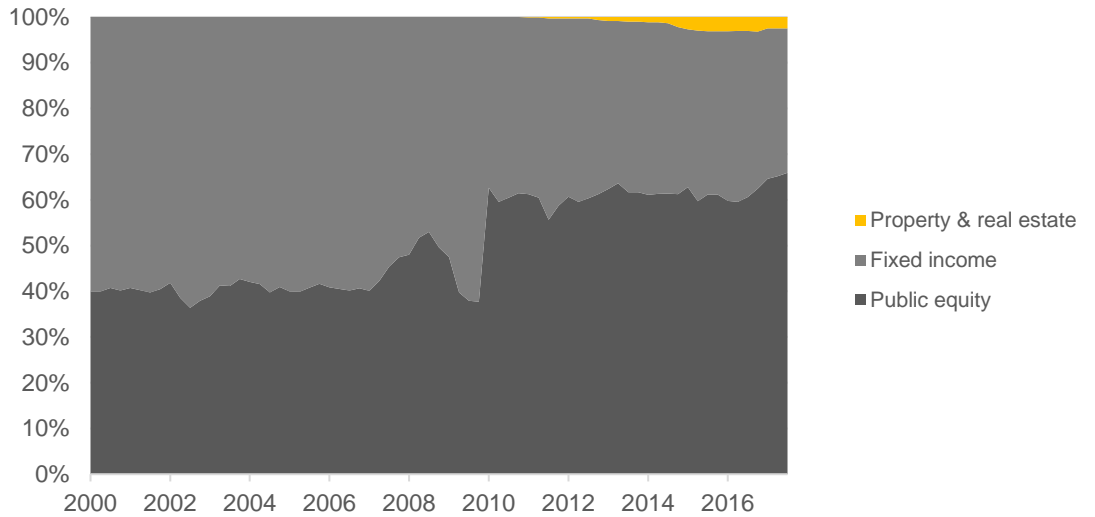


Figure D.1: Changes in asset class weights over time – GPFG

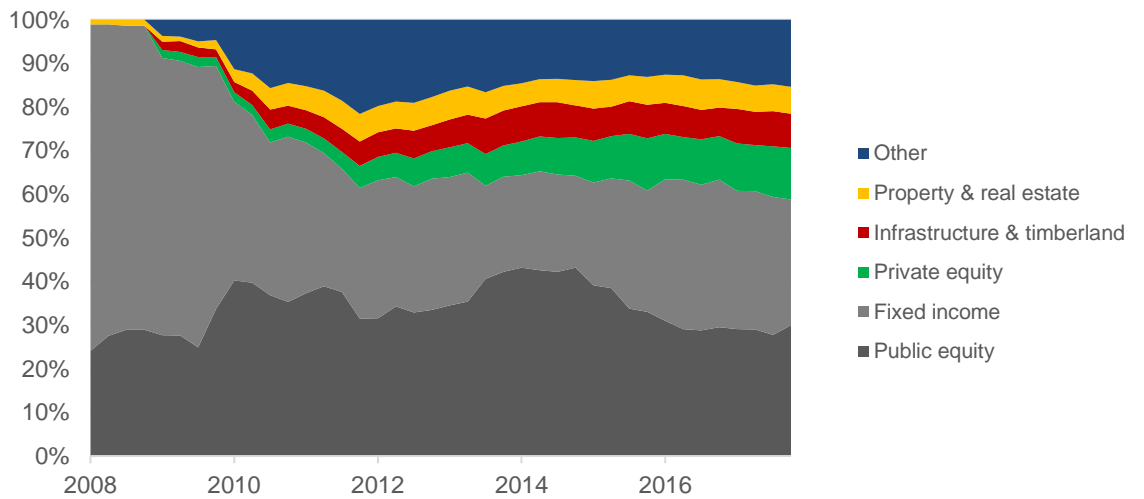


Figure D.2: Changes in asset class weights over time – FF

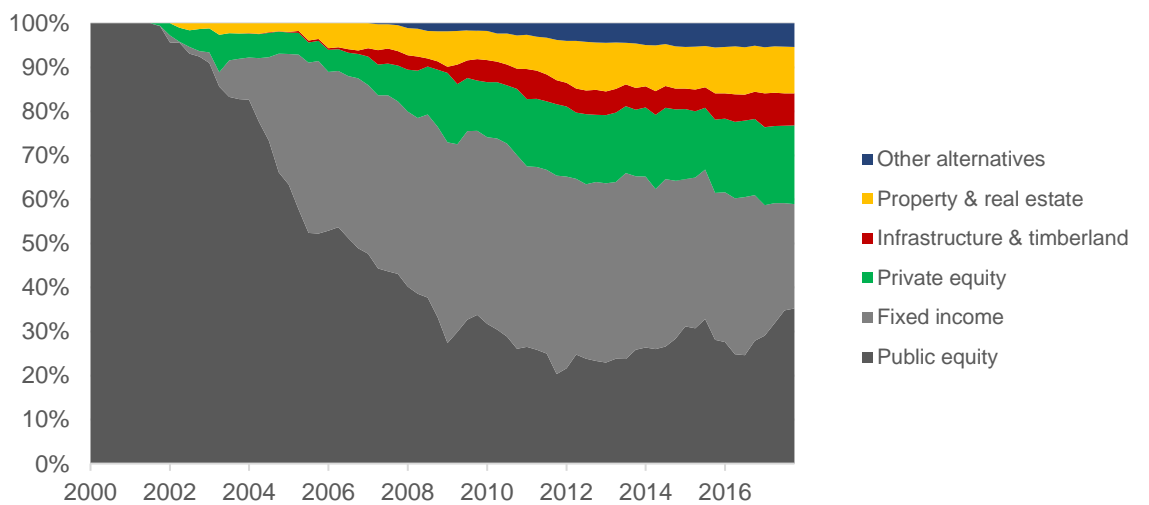


Figure D.3: Changes in asset class weights over time – CPP

Appendix E: Asset Class Returns Correlation by Fund

Table E.1: Correlation of investment returns by asset class within funds – GPF

Whole sample 2000-2017	Public equity	Fixed income	Property & real estate	Total return	Subsample 1 2000-2007	Public equity	Fixed income	Property & real estate	Total return	Subsample 2 2008-2017	Public equity	Fixed income	Property & real estate	Total return
Public equity	1.00				Public equity	1.00				Public equity	1.00			
Fixed income	-0.30	1.00			Fixed income	0.14	1.00			Fixed income	-0.41	1.00		
Property & real estate	-0.22	-0.09	1.00		Property & real estate	n.a.	n.a.	n.a.		Property & real estate	-0.22	-0.09	1.00	
Total return	0.65	0.51	-0.18	1.00	Total return	0.82	0.69	n.a.	1.00	Total return	0.59	0.48	-0.18	1.00

Table E.2: Correlation of investment returns by asset class within funds – CPP

Subsample 1 2000-2007	Public equity	Fixed income	Private equity	Infra. & timber	Property & real estate	Other	Total alternatives	Total return
Public equity	1.00							
Fixed income	-0.07	1.00						
Private equity	0.74	-0.15	1.00					
Infra. & timber	-0.51	-0.43	0.53	1.00				
Property & real estate	0.87	-0.22	0.88	-0.08	1.00			
Other	-0.92	-0.61	0.95	0.24	-0.62	1.00		
Total alternatives	0.83	-0.08	0.93	0.32	0.99	1.00	1.00	
Total return	0.99	-0.06	0.77	-0.49	0.91	-0.91	0.87	1.00

Subsample 2 2008-2017	Public equity	Fixed income	Private equity	Infra. & timber	Property & real estate	Other	Total alternatives	Total return
Public equity	1.00							
Fixed income	0.15	1.00						
Private equity	0.52	0.08	1.00					
Infra. & timber	0.24	0.09	0.85	1.00				
Property & real estate	0.43	0.12	0.87	0.92	1.00			
Other	0.09	0.23	0.13	0.03	0.09	1.00		
Total alternatives	0.50	0.11	0.98	0.91	0.95	0.14	1.00	
Total return	0.93	0.17	0.77	0.51	0.69	0.07	0.76	1.00

Table E.3: Correlation of investment returns by asset class within funds – FF

Subsample 2 2008-2017	Public equity	Fixed income	Private equity	Infra. & timber	Property & real estate	Other	Total alternatives	Total return
Public equity	1.00							
Fixed income	0.26	1.00						
Private equity	0.22	0.24	1.00					
Infra. & timber	0.12	-0.29	0.45	1.00				
Property & real estate	0.68	0.37	0.48	0.26	1.00			
Other	0.36	-0.19	0.50	0.50	0.57	1.00		
Total alternatives	0.47	0.01	0.67	0.64	0.73	0.96	1.00	
Total return	0.81	0.70	0.53	0.09	0.77	0.33	0.52	1.00

Appendix F: Excess Quarterly Return (PE)

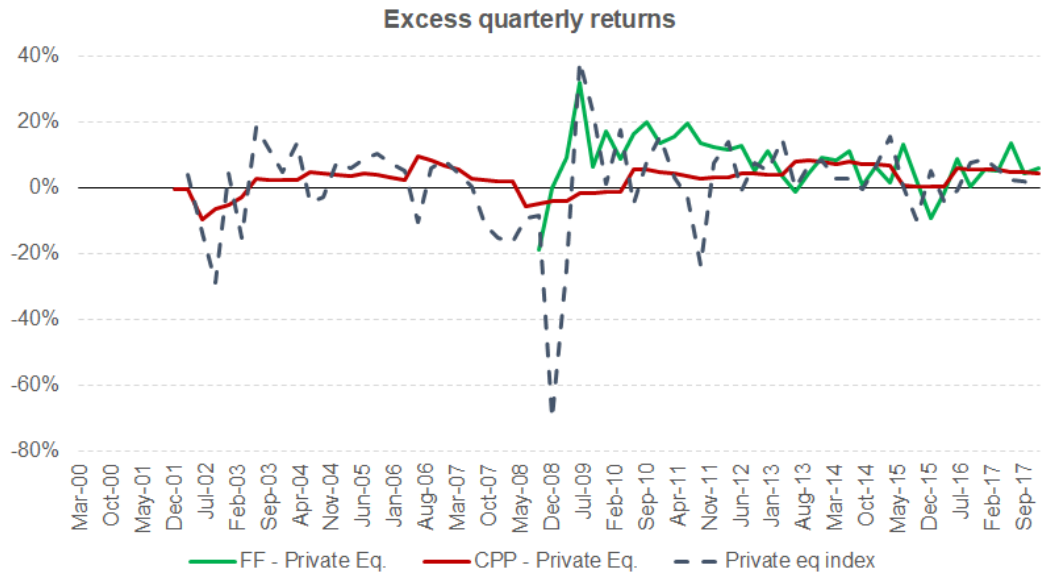


Figure F.1: Excess returns of fund's private equity asset class and index

Appendix G: CAPM Regressions

Table G.1: CAPM with two lags regression results

CAPM regression with two lags

Excess fund returns, gross of costs, p-value of estimate shown in brackets

	<u>FF</u>		<u>CPP</u>		<u>GPEG</u>	
	2000-2007	2008-2017	2000-2007	2008-2017	2000-2007	2008-2017
$\hat{\alpha}_i$	<i>n.a.</i>	0.0194**	-0.0060	0.0178**	0.0089	0.0077
	<i>n.a.</i>	(0.0038)	(0.319)	(0.0002)	(0.0596)	(0.0571)
$\hat{\beta}_{i,0}$	<i>n.a.</i>	0.8071**	0.6914**	0.2551**	0.3875**	0.6585**
	<i>n.a.</i>	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{\beta}_{i,1}$	<i>n.a.</i>	-0.0972	0.4443**	0.1180*	0.0867	0.0132
	<i>n.a.</i>	(0.2557)	(0.0030)	(0.0479)	(0.1959)	(0.8172)
$\hat{\beta}_{i,2}$	<i>n.a.</i>	-0.0167	-0.0916	0.1274*	0.0442	-0.0236
	<i>n.a.</i>	(0.8408)	0.5545	(0.0276)	(0.5241)	(0.6694)
$\hat{\beta}_{i,0} + \hat{\beta}_{i,1}$	<i>n.a.</i>	-0.1139	0.3527	0.2454	0.1310	-0.0104
$\hat{\beta}_{i,0} + \hat{\beta}_{i,1} + \hat{\beta}_{i,2}$	<i>n.a.</i>	0.6932	1.0441	0.5005	0.5184	0.6480
R^2	<i>n.a.</i>	0.7420	0.5148	0.5184	0.5667	0.8206

Table G.2: CAPM with two lags regression results, excluding alternative assets

CAPM regression with two lags, excluding alternative assets

Excess fund returns, gross of costs, p-value of estimate shown in brackets

	<u>FF</u>		<u>CPP</u>		<u>GPEG</u>	
	2000-2007	2008-2017	2000-2007	2008-2017	2000-2007	2008-2017
$\hat{\alpha}_i$	<i>n.a.</i>	0.0053	-0.0068	0.0160**	0.0089	0.0068
	<i>n.a.</i>	(0.2576)	(0.2307)	(0.0000)	(0.0596)	(0.0833)
$\hat{\beta}_{i,0}$	<i>n.a.</i>	1.0015**	0.5009**	0.1759**	0.3875**	0.6592**
	<i>n.a.</i>	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
$\hat{\beta}_{i,1}$	<i>n.a.</i>	-0.2146*	0.3163**	0.0734	0.0867	0.0125
	<i>n.a.</i>	(0.0254)	(0.0037)	(0.1033)	(0.1959)	(0.8282)
$\hat{\beta}_{i,2}$	<i>n.a.</i>	-0.0631	-0.0676	0.0690	0.0442	-0.0252
	<i>n.a.</i>	(0.4976)	(0.5490)	(0.1139)	(0.5241)	(0.6508)
$\hat{\beta}_{i,0} + \hat{\beta}_{i,1}$	<i>n.a.</i>	-0.2777	0.2487	0.1424	0.1310	-0.0127
$\hat{\beta}_{i,0} + \hat{\beta}_{i,1} + \hat{\beta}_{i,2}$	<i>n.a.</i>	0.7238	0.7497	0.3183	0.5184	0.6464
R^2	<i>n.a.</i>	0.7781	0.5096	0.4468	0.5667	0.8191

Table G.3: CAPM with three lags regression results

Subsample 2: 2008-2017

Excess fund returns, gross of costs, p-value of estimate shown in brackets

	FF	CPP	GPFG
$\hat{\alpha}_i$	0.0197** (0.0031)	0.0176** (0.0002)	0.0078 (0.0510)
$\hat{\beta}_{i,0}$	0.8005** (0.0000)	0.2597** (0.0000)	0.6539** (0.0000)
$\hat{\beta}_{i,1}$	-0.1087 (0.2030)	0.1260* (0.0344)	0.0053 (0.9259)
$\hat{\beta}_{i,2}$	0.0058 (0.9462)	0.1119 (0.0602)	-0.0082 (0.8851)
$\hat{\beta}_{i,3}$	-0.0768 (0.3497)	0.0531 (0.3535)	-0.0528 (0.3350)
$\hat{\beta}_{i,1} + \hat{\beta}_{i,2} + \hat{\beta}_{i,3}$	-0.1798	0.2910	-0.0557
$\hat{\beta}_{i,0} + \hat{\beta}_{i,1} + \hat{\beta}_{i,2} + \hat{\beta}_{i,3}$	0.6208	0.5506	0.5982
R ²	0.7483	0.5300	0.8253

Appendix H: Asymmetric CAPM Regressions

Table H.1: Asymmetric CAPM with two lags

Asymmetric CAPM regression with two lags

Excess fund returns, gross of costs, p-value of estimate shown in brackets

	<u>FF</u>		<u>CPP</u>		<u>GPF</u>
	2008-2017	2000-2007	2008-2017	2000-2007	2008-2017
$\hat{\alpha}_i$	0.0000 (0.4993)	0.0036 (0.4582)	0.0250** (0.0054)	0.0089 (0.2610)	0.0004 (0.4837)
$\hat{\beta}_{i,0}^{pos}$	0.8268** (0.0001)	0.8365* (0.0224)	0.4343** (0.0026)	0.6444** (0.0000)	0.8004** (0.0000)
$\hat{\beta}_{i,1}^{pos}$	0.0722 (0.7048)	0.5203 (0.1384)	-0.0626 (0.6279)	-0.1054 (0.4563)	-0.0368 (0.7763)
$\hat{\beta}_{i,2}^{pos}$	0.1462 (0.4178)	-0.4256 (0.1952)	0.0442 (0.7179)	0.0237 (0.8582)	0.0453 (0.7120)
$\hat{\beta}_{i,0}^{neg}$	0.7524** (0.0000)	0.5614* (0.0497)	0.1833 (0.0503)	0.2700* (0.0192)	0.5696** (0.0000)
$\hat{\beta}_{i,1}^{neg}$	-0.2150 (0.1254)	0.4594 (0.1047)	0.2655** (0.0052)	0.3197** (0.0051)	0.0597 (0.5309)
$\hat{\beta}_{i,2}^{neg}$	-0.0594 (0.6967)	0.1922 (0.4646)	0.1892 (0.0667)	-0.0582 (0.5826)	-0.0270 (0.7940)
R ²	0.7627	0.5509	0.5821	0.6756	0.8293

Table H.4: Asymmetric CAPM with two lags, excluding alternative assets

Asymmetric CAPM regression with two lags

Excess fund returns, gross of costs, p-value of estimate shown in brackets

	<u>FF</u>		<u>CPP</u>		<u>GPF</u>
	2008-2017	2000-2007	2008-2017	2000-2007	2008-2017
$\hat{\alpha}_i$	0.0059 (0.3641)	-0.0045 (0.4294)	0.0136* (0.0372)	0.0089 (0.2610)	-0.0017 (0.4327)
$\hat{\beta}_{i,0}^{pos}$	0.9761** (0.0001)	0.6404* (0.0163)	0.3250** (0.0036)	0.6444** (0.0000)	0.8090** (0.0000)
$\hat{\beta}_{i,1}^{pos}$	-0.1481 (0.5061)	0.4047 (0.1135)	-0.0289 (0.7730)	-0.1054 (0.4563)	-0.0281 (0.8286)
$\hat{\beta}_{i,2}^{pos}$	-0.1110 (0.5983)	-0.2835 (0.2361)	0.0973 (0.3039)	0.0237 (0.8582)	0.0498 (0.6854)
$\hat{\beta}_{i,0}^{neg}$	1.0188** (0.0000)	0.3787 (0.0691)	0.0947 (0.1920)	0.2700* (0.0192)	0.5639** (0.0000)
$\hat{\beta}_{i,1}^{neg}$	-0.2560 (0.1183)	0.3141 (0.1278)	0.1573* (0.0326)	0.3197** (0.0051)	0.0537 (0.5741)
$\hat{\beta}_{i,2}^{neg}$	-0.0286 (0.8722)	0.1290 (0.5004)	0.0778 (0.3303)	-0.0582 (0.5826)	-0.0271 (0.7942)
R ²	0.7791	0.5453	0.4942	0.6756	0.8288

Appendix I: Canada Return Attribution

Table I.1: Canada return attribution regressions for public equity and fixed income, unrestricted regression

<u>Subsample 2: 2008-2017</u> <i>Excess fund returns, gross of costs</i>	<u>CPP Public</u> <u>Equity</u>	<u>CPP Fixed</u> <u>Income</u>
$\hat{\alpha}_i$	<i>0.0106</i> <i>(0.0503)</i>	<i>0.0104**</i> <i>(0.0050)</i>
$\hat{\beta}_{i, PubEq}$	<i>-0.5362</i> <i>(0.0925)</i>	<i>-0.0068</i> <i>(0.9727)</i>
$\hat{\beta}_{i, FI}$	<i>0.2392</i> <i>(0.4276)</i>	<i>0.3767*</i> <i>(0.0457)</i>
$\hat{\beta}_{i, RE}$	<i>-0.0321</i> <i>(0.7961)</i>	<i>0.0451</i> <i>(0.5610)</i>
$\hat{\beta}_{i, PrivEq}$	<i>0.3077*</i> <i>(0.0285)</i>	<i>0.0389</i> <i>(0.6573)</i>
$\hat{\beta}_{i, Infra}$	<i>0.5488</i> <i>(0.0674)</i>	<i>-0.2111</i> <i>(0.2603)</i>
$\hat{\beta}_{i, Other}$	<i>0.0240</i> <i>(0.9539)</i>	<i>0.2436</i> <i>(0.3467)</i>
R^2	<i>0.6283</i>	<i>0.1529</i>