
An EDHEC-Risk Institute Publication

Benefits of Open Architecture and Multi-Management in Real Estate Markets— Evidence from French Nonlisted Investment Trusts

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in partnership with



1. Introduction	5
2. Institutional Aspects of French Commercial Real Estate Investment Funds	9
3. Dataset and Statistical Treatments	21
4. SCPI Risk and Performance Analysis	43
5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection	53
6. Portfolio Diversification and Benefits of Allocation	71
7. Conclusion	83
References	87
About Swiss Life Asset Managers France	91
About EDHEC-Risk Institute	93
EDHEC-Risk Institute Publications (2019-2021)	97



Foreword

This publication was produced in partnership with Swiss Life Asset Managers France as part of the “Real Estate in Modern Investment Solutions” research chair at EDHEC-Risk Institute, which examines the role of real estate in welfare-improving forms of investment solutions, with a particular focus on the efficient use of dedicated real estate investments as part of the performance and hedging components of innovative retirement solutions. This study, “Benefits of Open Architecture and Multi-Management in Real Estate Markets—Evidence from French Nonlisted Investment Trusts”, reviews the risk and return characteristics of *Sociétés Civiles de Placement Immobilier* (SCPIs), a form of French non-listed real estate funds, to assess whether modern investment management techniques can be applied to this growing universe of investment vehicles.

We find that the commercial SCPI market offers a significant amount of dispersion in risk and return, and portfolios of SCPIs exhibit a substantially lower level of volatility than the “average SCPI”. We also find several attributes to have explanatory power with respect to such differences in risk and performance. Both results suggest that value can be added by selection and allocation decisions, which could form the basis of a welfare-enhancing open architecture multi-management approach to investment in SCPIs.

We would like to thank the *Institut de l'Épargne Immobilière et Foncière* (IEIF) for kindly sharing their extensive dataset, Pierre Schoeffler, Senior Advisor at IEIF for his insights on liquidity matters, Vincent Milhau, Research Director at EDHEC-Risk Institute, for his very useful comments on statistical matters, Hossein Kazemi, Professor of Finance at the Isenberg School of Management at the University of Massachusetts, Amherst, for his insights on the handling of illiquid and infrequent performance data, Alain Pivert, real estate specialist at Amadeis, for his expert opinion on the SCPI market, and Laurent Ringelstein for his efforts in producing the final publication. More generally, we would also like to extend our thanks to Swiss Life Asset Managers France for their support of this research chair.

We wish you a useful and informative read.



Béatrice Guedj
Head of Research and Innovation,
Swiss Life Asset Managers France



Lionel Martellini
Professor of Finance,
Director of EDHEC-Risk Institute



Shahyar Safaee
Research Engineer,
EDHEC-Risk Institute

ABOUT THE AUTHORS



Béatrice Guedj is Head of Research & Innovation at Swiss Life Asset Managers (SLAM). She holds a PhD in Quantitative Economics. Béatrice has been in the real estate research and strategy fields in Europe for more than 20 years, involved in Real Estate Asset Allocation and Quantitative Research for Institutional Investors and Sovereign Wealth Funds. She was Managing Director of Grosvenor Fund Management in Continental Europe for 12 years. Béatrice remains highly involved to key bodies such as senior advisor at the Institut de l'Épargne Immobilière et Foncière and is co-manager of the REFINE network of academic research on commercial real estate hosted at Institut Louis Bachelier to promote quantitative research in the property industry.



Lionel Martellini is Professor of Finance at EDHEC Business School and Director of EDHEC-Risk Institute. He has graduate degrees in economics, statistics, and mathematics, as well as a PhD in finance from the University of California at Berkeley. Lionel is a member of the editorial board of the *Journal of Portfolio Management* and the *Journal of Alternative Investments*. An expert in quantitative asset management and derivatives valuation, his work has been widely published in academic and practitioner journals and he has co-authored textbooks on alternative investment strategies and fixed-income securities.



Shahyar Safae is a research engineer at EDHEC-Risk Institute. He holds master's degrees in engineering (Ecole des Mines de Saint-Etienne) and financial mathematics (Université Claude Bernard in Lyon). Before joining EDHEC-Risk Institute in 2020, Shahyar was a capital markets professional with a 20-year track record in both sell-side and buy-side roles, notably spending 18 years in J.P. Morgan's Global Equities division in London, Paris, and New York, serving institutional clients in various capacities including quantitative research, trading, fund management, and structuring.

1. Introduction

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Real estate has become an essential part of institutional investment portfolios. According to a global survey of institutional investors by Schroders in 2020¹, one in five (18%) investors allocates between 5–10% of their overall portfolio toward real estate, while one in eight (13%) allocates over 10%. More than three-quarters of the institutional investors surveyed are driven by the prospect of higher returns (79%) and portfolio diversification (78%) when investing in private assets such as real estate.

This is consistent with the arguments generally put forward by investment management professionals to view real estate equity as an asset class. These arguments are summarized as follows in Ducoulombier (2007): (1) Sufficient size: the real estate market is deep enough to support a 10% or greater allocation in an efficient mixed-asset portfolio; (2) Competitive returns: 4–6% average annual real rates of returns over long-term horizons combined with a low volatility leading to attractive risk-adjusted performance over time; and (3) Unique return characteristics: low correlation to other major asset classes over long-term horizons (making real estate a diversifying addition to traditional portfolios), inflation-hedging capabilities over time, and a large current income component driving total returns.

Ducoulombier (2007) also listed portfolio diversification and attractive risk-adjusted returns as the top two reasons cited by investors that were not real estate specialists, so these investment rationales seem to have withstood the test of time.

Overall, real estate investing is now established as a source of diversification and added value in the context of multi-class portfolio construction.

More precisely, we argue that it has the potential to enhance not only the performance-seeking portfolio of modern liability-driven or goal-based investing solutions, where it brings diversification benefits, but also the liability- or goal-hedging portfolio, based on its ability to generate inflation-linked cash flows over long horizons.

However, achieving efficient real estate exposure in practice has often been a challenge because of the idiosyncratic features of the asset class: high unit value (indivisibility), heterogeneity, fixed (location-specific) nature, and the need for day-to-day property management. Indeed, these features have several practical implications for real estate investing. In particular, no liquid market exists for an individual real estate asset. Besides, property management is a large contributor to the value of real estate assets, and specific risk is a large contributor to the overall risk of a given real estate asset. Finally, diversification (geographic or sectoral) can be challenging for it may hinder economies of scale in property management.

As a result, a variety of real estate investment vehicles have been designed over time to match investors' needs and provide solutions to some or all of the challenges identified above that are typical of direct investing.

Private vehicles, either private companies or private equity-like funds, enhance the direct physical investment approach in that they bring diversification and optimise property management through professionalisation and some economies of scale. However, they do not address issues such as illiquidity or, to some extent, indivisibility. Publicly registered exchange-traded vehicles, such as real estate operating companies or more

1 - Schroders, Institutional Investor Study 2020 – Private Assets: <https://www.schroders.com/en/sysglobalassets/digital/institutional-investor-study-2020/private-assets/pdf/SIIS-PRIVATE-ASSETS-2020-IL.pdf>

1. Introduction

recently *Real Estate Investment Trusts* (REITs), were developed to provide investors with a liquid way of accessing property ownership with a small unit investment value. Although REITs seem to satisfy all or most of the requirements of investors – except perhaps for agency problems, which are generally pervasive to all fiduciary relationships – their liquidity comes at a cost and indirectly results in unwanted short-term volatility and a strong short-term correlation with equity markets, thus seriously impinging on the diversification benefits that first motivated the investment. As explained in Ducoulombier (2007), the price of an REIT listed on a stock exchange will reflect microeconomic expectations, as well as views on attributes common to the listed real estate sector and to the market as a whole. The REIT price therefore becomes a function of continuously fluctuating market expectations and risk preferences and ends up, in the short term, moving somewhat in tandem with the overall equity market.

Publicly registered *non-listed* vehicles aim to follow a “Third Way” by striking a balance between liquidity and decorrelation from traditional asset classes, in order to give the best of both worlds to investors, namely a regulated public vehicle whose shares are transferable, thus providing some liquidity (albeit a limited amount) compared to private funds, as well as a vehicle whose performance and risk profiles are reflective of the underlying real estate physical assets, displaying little correlation with equity markets (see Ducoulombier (2007)). Examples of such public but non-listed funds include the public non-traded REIT in the US, its counterpart in France known as *Société Civile de Placement Immobilier* (SCPI), and the German open-end real

estate funds (although shares of the latter can also be traded on stock exchanges; see Gerlach and Maurer (2020) for further details).

The use of non-listed real estate collective investment schemes has been widely explored and analysed in academic and industry research. A lot of the literature is region- or country-specific due to the nature of the asset class and the different regulatory regimes applicable globally.

For instance, Brounen et al. (2007) provide a description of the European universe of non-listed real estate funds, viewing it as an alternative route to real estate exposure by enabling diversification, avoiding exposure to general stock market volatility, and offering some limited liquidity. Fuerst and Matysiak (2013) conduct an empirical panel analysis of the performance of European non-listed real estate funds, identifying the drivers of total returns across funds as well as over time. Delfim and Hoesli (2016) identify and assess the risk factors impacting the performance of European non-listed real estate funds, and report that the latter are more akin to direct real estate investment than they are to listed real estate. A general introduction to US public non-listed REITs is provided by Hogan (2013). In a more academic framework, Seguin (2016) performs a valuation of US public non-listed REITs relative to their listed counterparts based on fundamental financial analysis and concludes that non-listed US REITs should trade at a large discount due to their lower liquidity, higher transaction costs and sub-optimal structures, ultimately questioning the suitability of US non-listed REITs for investors. A new type of non-listed REITs (“perpetual REITs” or “NAV REITs”) has been developed in the US to address some of these concerns.

1. Introduction

Fund selection and portfolio allocation decisions are two long-standing research topics within traditional asset classes like equities and bonds and are recognized as important sources of improved risk-adjusted returns for investors. The two topics have also been addressed specifically in the academic literature on real estate investments and particularly non-listed real estate funds.

Bond and Mitchell (2010) consider the key question of selection by analysing IPD data of UK non-listed property funds and conclude there is little evidence of managers systematically and persistently delivering superior risk-adjusted returns, and also little evidence that poor performance is persistent. Aarts and Baum (2016) investigate performance persistence across real estate private equity funds and find strong evidence of persistence between directly consecutive funds, but little evidence over longer-term horizons.

Seiler et al. (1999) cover portfolio allocation by presenting a review of the literature on diversification within the real estate asset class and highlighting that academics and practitioners have considered the benefits of diversification across several dimensions including size, property type, or geographic and economic region. Jadevicius (2019) makes the case for portfolio allocation in the global non-listed real estate market by showing the benefits of diversification in synthetically constructed portfolios of non-listed real estate vehicles operated in the US, Europe and Asia.

To the best of our knowledge, there is no published research focusing on French non-listed real estate

vehicles to the notable exception of Schoeffler (2020), who conducts a review of open-end non-listed French property funds, examines their inherent liquidity risk as well as the mechanisms in place to both manage such risk and have it accurately priced.

The objective of this paper is to analyse whether traditional investment management techniques such as fund selection and portfolio allocation can be applied to the SCPI universe and create value for an investor wishing to be exposed to French non-listed commercial real estate. Our goal is therefore to look for elements and features of the SCPI universe that suggest there are benefits in applying selection and allocation techniques to SCPIs. We do not, however, intend to address the implementation of such techniques or design an investment portfolio construction methodology.

The rest of the paper is organized as follows. Section 2 introduces readers to the French non-listed property fund market and the SCPI vehicle. Section 3 is dedicated to the SCPI dataset analysed in this paper, the challenges posed by real estate market data in general, and the statistical methods used to address them. The remaining three sections focus more specifically on the main objective of the paper by describing the cross-sectional dispersion of risk and return profiles within the SCPI universe (Section 4), searching for SCPI attributes that may explain such cross-sectional dispersion (Section 5) and assessing the effects of diversification when investing in SCPIs (Section 6). Finally, our conclusions and suggestions for extension can be found in Section 7.

2. Institutional Aspects of French Commercial Real Estate Investment Funds

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This section aims to introduce readers to the French non-listed commercial property fund market, focusing specifically on the SCPI vehicle. First, we present the French commercial real estate market and the non-listed fund vehicles it offers to investors. We then describe the SCPI fund vehicle and briefly review its regulatory environment. In the third part, we provide an overview of the SCPI market and recent changes. In the fourth and final part of this section we cover the valuation and secondary market processes applicable to SCPIs and the liquidity risk of an SCPI investment, and conclude with a brief recap of the standard trade-off between liquidity and decorrelation in real estate markets.

2.1 Public Commercial Real Estate Investment Vehicles in France

According to the European Public Real Estate Association (EPRA), at the end 2019 the size of the global commercial real estate market was \$31tn.² The overall figure can be broken down into four large geographical segments: North America (32%, with the US representing 29%), Europe (27%), Developed Asia (14%) and Emerging Markets (27%).

In Europe around 35% of all commercial property was held as an investment, amounting to approximately \$3tn, of which public non-listed real estate investment vehicles represented close to a third (29%), while listed (exchange-traded) property companies and REITs represented one-fifth (19%).³ The remaining portion (52%) comprised privately placed investments and vehicles. In comparison, the size of the US REIT market was \$3.5tn in terms of gross assets, with

36% held by public exchange-traded REITs, 36% by public non-listed REITs and 29% by private REITs (i.e. not subject to SEC registration).⁴

France accounts for approximately 15% of the European commercial real estate market.⁵ Real estate companies have long operated in France. The very first one was Société Foncière Lyonnaise, established in 1879 with roots in the financial industry. Its founder Henri Germain, whose ideas about banking and liquidity would eventually inspire the Glass-Steagall Act, had created Crédit Lyonnais only a few years before. The most glamorous French real estate company was perhaps the Société de La Tour Eiffel, founded by Gustave Eiffel himself in 1885 to manage the soon-to-be-built eponymous tower. Today, most French listed property companies (92%) have, since 2003, opted for a transparent tax status very similar to the REIT regime and are known as Société d'Investissement Immobilier Cotée (SIIC). These "French REITs" trade on organised exchanges and are primarily exposed to commercial real estate (the main index representative of French REITs, the Euronext IEIF SIIC France Index, had less than 7.5% of residential exposure as of October 2020⁶). The market capitalisation of French REITs amounted to \$87.2bn at the end of 2019.

Turning to non-listed investment vehicles, all French non-listed public real estate investment funds are regulated financial products. Officially, they are unlisted *Alternative Investment Funds* (AIF), governed by the European AIFM Directive. They raise capital from institutional or private investors and allocate it to real estate assets which they subsequently manage and let in order to collect rental income. They may specialize

2 - EPRA, Global Real Estate Total Markets Table 2019: https://prodapp.epra.com/media/EPRA_Total_Markets_Table_-_Q4-2019_1580381101760.pdf

3 - INREV and EPRA, Real Estate in the Real Economy 2020: <https://www.inrev.org/system/files/2020-11/INREV-EPRA-Real-Estate-Real-Economy-2020-Report.pdf>

4 - National Association of Real Estate Investment Trusts (Nareit): <https://www.reit.com>, <https://www.reitsacrossamerica.com/united-states>

5 - EPRA, *op. cit.*

6 - EDHEC-Risk Institute estimate, IEIF October 2020: <https://www.ieif.fr/actualites/les-chiffres-cles-des-siic>

2. Institutional Aspects of French Commercial Real Estate Investment Funds

or diversify in different classes of real estate assets (commercial properties such as offices, retail units, shops, hotels, business premises and warehouses, and residential properties) as well as in different geographical areas (France and Europe). Their underlying real estate assets are managed by an investment management company (IMC) authorized by the *Autorité des Marchés Financiers* (AMF), the French financial market regulator whose responsibilities can be compared to those of the Securities and Exchange Commission in the US or the Financial Conduct Authority in the UK. The IMC acts on behalf of investment funds: it makes investments, manages leases, carries out maintenance and improvements, and performs administrative, accounting and tax duties.

The funds can take different forms to cater for the various needs of investors. With respect to vehicles that are available to all investors, including retail investors, a key distinction exists between two types of products. The first is **SCPIs** (*Sociétés Civiles de Placement Immobilier*), which were introduced in 1964. They are tax-transparent vehicles (like REITs) and are subject to the rules governing real estate income and capital gains tax in France. By regulation, their portfolio needs to be exclusively made up of real estate assets (direct or indirect) and money market instruments (cash, deposits, FX). Financial leverage is allowed but needs to be formally approved by investors who decide on a loan-to-value (LTV) cap at general meetings, generally between 20 and 40%.

At the end of 2018, the average effective LTV ratio across all SCPIs was slightly above 15%, with 8%

of the universe exceeding a 30% LTV. The recent trend has seen an increase in financial leverage: the average effective LTV ratio was only 7.7% in 2016, with 3% of the universe exceeding a 30% LTV.⁷ The total assets under management (AUM) of SCPIs at the end 2019 amounted to \$73bn and the 97 SCPI vehicles specialised in commercial real estate represented about 94% of the total AUM.⁸ The SCPIs specialised in residential property were equally large in number (94 vehicles) but much smaller in size (\$4.7bn, 6% of SCPI AUM); these are primarily driven by specific tax incentives ("Scellier", "Robien", "Malraux", "Pinel", etc) only available to French fiscal residents and are outside the scope of our paper. The second type is **OPCI**s (*Organismes de Placement Collectif en Immobilier*), which were introduced more recently, in 2007. They too are tax-transparent but fall under the tax rules governing the income and capital gains of financial securities. By regulation, real estate assets need to comprise at least 60% of their portfolio, which means OPCIs can practically diversify into other assets classes such as listed equities and bonds, which is their main difference with respect to SCPIs. The intention here is to allow OPCIs to run a more liquid portfolio which would in turn facilitate redemptions when and if investors wish to exit the fund. The regulations allow OPCIs to use leverage up to certain limits (40% LTV on real estate assets and 10% LTV on other assets) but also require them to comply with a set of concentration limits to ensure their portfolio is sufficiently diversified. 18 OPCI vehicles were operating at the end of 2019, with total AUM of \$20.8bn.⁹

In addition to SCPIs and OPCIs, there are also vehicles available to professional investors only

7 - <https://www.meilleurescpi.com/>

8 - IEIF database, Pierre Papier : <https://www.pierrepapier.fr/>

9 - IEIF, Pierre Papier, *op. cit.*

2. Institutional Aspects of French Commercial Real Estate Investment Funds

known as **OPPCIs** (*Organismes Professionnels de Placement Collectif Immobilier*). The OPPCI is the institutional version of the OPCI. The two vehicles are sometimes called "professional OPCI" and "retail OPCI" for that reason. The notable differences with the (retail) OPCI are the absence of regulatory leverage and portfolio concentration limits, although some limits may be self-imposed and formalised in the fund's legal documentation. The majority of OPPCIs are structured as bespoke mandates. 305 OPPCI vehicles were operating at the end of 2019, with total AUM of \$55.3bn.¹⁰

Our paper will exclusively focus on (commercial) SCPIs. The reason is twofold. First, unlike OPCIs and OPPCIs, SCPIs are purely exposed to real estate and their performance is therefore not impacted by other asset classes. Second, SCPIs have been operating for a much longer time so there is substantially more historical data available to analyse. We would also argue that SCPIs are more representative than listed French REITs (SIICs) of the overall French commercial real estate investment market. Unlike SCPIs, the former have a material exposure bias towards retail units compared to the overall commercial real estate market. This overall market's exposures to retail and offices are respectively 21%¹¹ and 60%¹² while those of the French REIT market (represented by the Euronext IEIF SIIC France Index) are respectively 45%¹³ and 26%¹⁴, and those of the SCPI market (represented by the EDHEC IEIF Commercial Property (France) Index) are respectively 20%¹⁵ and 68%.¹⁶

2.2 The SCPI Regulated Vehicle

The SCPI's purpose is to acquire, develop, own and manage real estate assets in order to generate rental income. Its governance is subject to the oversight of the AMF and is structured around the following four stakeholders. First, the **IMC** (Investment Management Company) is specifically approved by the AMF to manage SCPI vehicles. It makes investments, manages leases, carries out maintenance and improvements, and performs administrative, accounting and tax duties. Second, the **custodian** (also called Depository, or *dépositaire* in French) is authorised and regulated in the European Union. Its main missions are safekeeping cash and financial instruments, overseeing real estate assets and the economic benefits (including cash flows) associated with their ownership, and ensuring regulatory compliance of any decision made by the SCPI or IMC. Third, the **independent real estate appraiser** is appointed at a general meeting of shareholders for a 5-year mandate, subject to the AMF's approval. The appraiser must formally declare to the AMF that it is independent of the IMC and of any real estate professional (developer, promoter, contractor, etc.) the SCPI may be dealing with. The AMF may at any time determine that an appointed appraiser is no longer suitable and request that the IMC seek a new appraiser. Finally, the **auditor** is appointed at a general meeting of shareholders for a 6-year mandate.

Additionally, the AMF reviews the offering documents of an SCPI prior to its market distribution, ensuring the information provided to investors is accurate.

10 - IEIF, Pierre Papier, *op. cit.*

11 - EDHEC Risk Institute, Oct 2020 estimate, IEIF database, Schoeffler (2020)

12 - EDHEC-Risk Institute, Dec 2019 estimate, French High Council for Financial Stability (HCSF), BNP Paribas Real Estate

13 - EDHEC-Risk Institute, HCSF, BNP Paribas, *op. cit.*

14 - EDHEC-Risk Institute, Oct 2020 estimate, IEIF: <https://www.ieif.fr/actualites/les-chiffres-cles-des-siic>

15 - EDHEC-Risk Institute, IEIF, *op. cit.*

16 - EDHEC Risk Institute, IEIF, Schoeffler *op. cit.*

2. Institutional Aspects of French Commercial Real Estate Investment Funds

There are two types of SCPIs, namely **closed-end** (*SCPI à capital fixe*) and **open-end** (*SCPI à capital variable*) funds. The management company of a closed-end SCPI may from time to time carry out a capital increase, but outside such subscription periods shares can only be acquired and sold on a secondary market organised by the management company. In contrast, an open-end SCPI operates like a company with variable capital; issuance of new shares or retirement of existing shares can happen at any time in order to meet subscription and redemption requests from investors. At the end of 2019, open-end SCPIs (*SCPI à Capital Variable*) represented respectively 91% and 75% of the overall SCPI universe in terms of AUM and number of vehicles.¹⁷ This was markedly different to the state of the SCPI market a decade prior: at the end of 2008, open-end SCPIs only represented 46% of AUM and 32% of vehicles. The change was largely the result of a trend of conversion from closed-end to open-end initiated by IMCs willing to capture the substantial capital inflows into the SCPI asset class.

Regulation specifies the types of fees and charges SCPI investors may face. Below is the list of fees an IMC is authorised to collect (although not every type of fee will be applicable to every SCPI)¹⁸:

- *subscription fee* (for an open-end SCPI or a capital increase of a closed-end SCPI) paid upfront by the buyer to the IMC, generally a percentage of the amount invested
- *secondary transaction fee* (for a closed-end SCPI) paid upfront by the buyer to the IMC, generally a percentage of the secondary transaction amount
- *management fee* paid annually by the SCPI to the IMC, generally a percentage of the annual rental income generated by the SCPI's assets

- *real estate acquisition or divestment fee* paid by the SCPI to the IMC, generally a percentage of the real estate transaction amount
- *property maintenance fee* paid by the SCPI to the IMC, generally a percentage of actual property maintenance expenses

Although no exact replica of the SCPI exists in the US real estate investment landscape, the closest equivalent would be the publicly registered non-exchange traded REIT, also known as Public Non-Listed REIT (PNLR), or just "non-traded REIT" for short. More specifically, SCPIs are similar to a certain category of non-traded REITs, namely the perpetual-life vehicles known as NAV REITs, which were developed more recently to address the historical concerns and shortcomings (see Seguin (2016)) of the first generation of finite-life non-traded REITs (also known as lifecycle REITs) introduced in the 1990s. Concerns included lack of liquidity and transparency, and questionable practices like distributions funded from principal or debt.¹⁹

NAV REITs have gained in popularity lately²⁰ due to their more investor-friendly and institutional-quality features²¹ and the recent launch of flagship NAV REIT vehicles by leading asset managers such as Blackstone, Starwood Capital and Oaktree. According to the National Real Estate Investor, perpetual life NAV REITs grabbed 93% of the new capital raised in 2019 by the non-traded REITs market versus the 7% that went to lifecycle peers.

2.3 The Commercial SCPI market

The market for SCPIs specialised in commercial real estate experienced significant growth in the

¹⁷ - IEIF database

¹⁸ - AMF, Règlement Général, Article 422-224.

¹⁹ - Troianovski, A. and C. Karmin, 29 June 2011, Nontraded REITs Are Put on Notice by SEC, *Wall Street Journal*

²⁰ - Nareit: <https://www.reit.com/news/reit-magazine/september-october-2018/evolution-public-non-listed-reit-pnlr>

²¹ - Goodwin, 2020, The Past, Present and Future of the Non-Traded NAV REIT Structure: https://www.goodwinlaw.com/publications/2020/01/01_23-the-past-present-and-future-of-non-traded#_ftn1

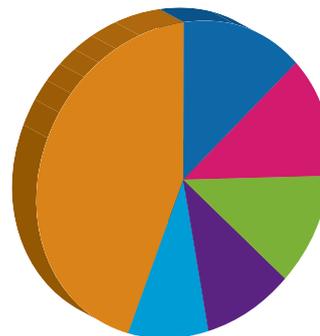
2. Institutional Aspects of French Commercial Real Estate Investment Funds

last decade, reaching AUM of \$68.3bn across 97 vehicles at the end of 2019 (see Exhibit 1). During the 2009–2019 period, the AUM almost quadrupled (3.6x) in local currency terms, translating into an average compounded annual growth rate of 13.6%, with approximately 90% of the growth (12.3%) explained by capital inflows and the remaining 10% (1.3%) driven by price performance. It is generally accepted that the expansion (both in size and in composition) of the European Central Bank’s quantitative easing policy (via the Asset Purchase Programme) from 2015 onwards contributed to the capital inflows seen in European “risk assets” in general, including real estate investment vehicles.

The governance of an SCPI (described in Section 2.2) implies that it is an externally-managed fund, whereby one asset manager could in principle manage several SCPIs. This creates potential for economies of scale, and the SCPI market features some level of concentration as a result. We note

that the 97 funds are run by 35 IMCs at the end of 2019, and the 5 largest IMCs manage 56% of the total AUM.

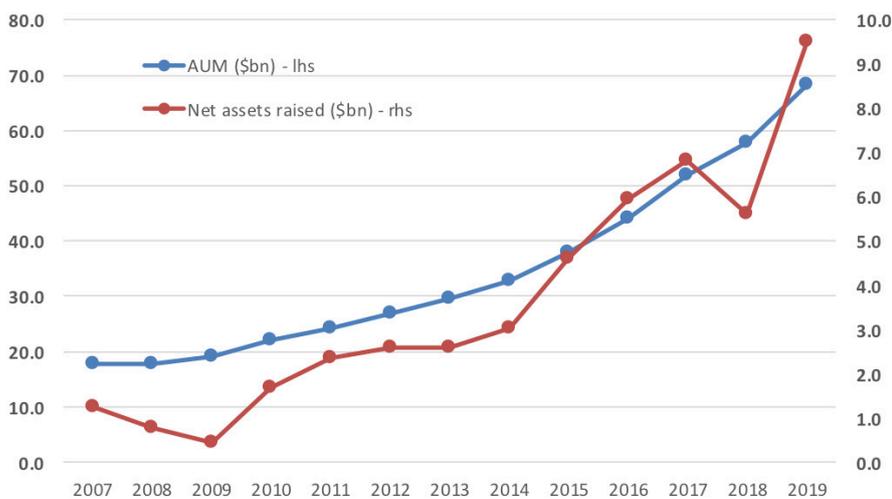
Exhibit 2: Distribution of the AUM of the commercial SCPI market by asset manager at the end of 2019



La Française REM 14%
 Amundi Immobilier 12.8%
 Primonial REIM 11.1%
 AEW Ciloger 9.4%
 BNP Paribas REIM France 9%
 Other Managers 43.7%

Notes: The pie chart represents the breakdown by asset manager of the AUM of the commercial SCPI market at the end of 2019. The blue, red, green, purple and turquoise slices each represent a single asset manager, while the orange slice represents the rest of the market.
 Source: Pierre Papier (<https://www.pierrepapier.fr/>)

Exhibit 1: Growth of AUM and Net assets raised observed in the commercial SCPI market from 2007 to 2019



Notes: The solid blue line (lhs) represents the 2007–2019 evolution of the AUM of the commercial SCPI market while the solid red line (rhs) represents the 2007–2019 evolution of the net annual assets raised (where net assets raised is equal to subscriptions minus redemptions).
 Sources: IEIF (<https://www.ieif.fr/>), Pierre Papier (<https://www.pierrepapier.fr/>)

2. Institutional Aspects of French Commercial Real Estate Investment Funds

Commercial SCPIs vary in size, in asset class strategy and in fees. The median AUM of the universe is \$570m with fund sizes ranging from \$1m to \$4bn. The 10 largest commercial SCPIs (each between \$2.5 and 4bn in net assets) collectively represent close to half (47%) of the total AUM at the end of 2019. The median upfront subscription fee across the commercial SCPI universe is 10%, with levels ranging between 0% and 14%, and the median annual management fee as a percentage of rental income is 10%, with levels ranging between 3% and 18%.

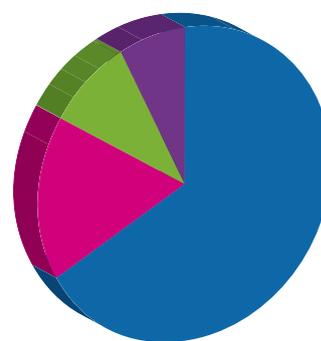
Strategy-wise, commercial SCPIs can focus on different classes of commercial real estate assets such as offices, retail shops, hotels, industrial premises, warehouses, medical centres, etc. The two most common areas of focus are Office and Retail, so the *Institut de l'Épargne Immobilière et Foncière* (IEIF, the leading independent research organization covering the French real estate investment market) has segmented the universe into four SCPI asset categories:

- 'Office': SCPIs with more than 70% exposure to offices
- 'Retail': SCPIs with more than 70% exposure to retail units
- 'Specialised': SCPIs with more than 70% exposure to asset classes other than Office or Retail (e.g. logistics, healthcare, hotels, etc.)
- 'Diversified': all other SCPIs (which are, by definition, somewhat diversified across Office, Retail and Specialised exposures)

As shown in Exhibit 3, the Office SCPIs represent by far the largest asset category in terms of AUM, with approximately two-thirds of the market. They are followed by the Diversified category

(17% of AUM), then Retail (9%) and finally Specialised (7%). This breakdown is consistent with the underlying real estate asset composition of the overall commercial SCPI market, which is dominated by offices.

Exhibit 3: Distribution of the AUM of the commercial SCPI market by asset category at the end of 2019



SCPI - Office **67%**
SCPI - Diversified **17%**
SCPI - Retail **9%**
SCPI - Specialised **7%**

Notes: The pie chart represents the breakdown by asset category of the total commercial SCPI AUM at the end of 2019. The blue, red, green and purple slices respectively represent the AUM of the Office, Diversified, Retail and Specialised categories as a percentage of the total commercial SCPI AUM.

Source: IEIF database

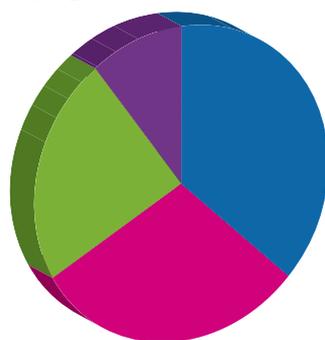
However, the distribution by number of funds shows a more balanced picture, offering investors the ability to select from a diverse set of vehicles (see Exhibit 4). This is due to Office SCPIs being on average 2.5 to 4.5 times larger in AUM than SCPIs belonging to the other asset categories.

SCPI vehicles are available to retail investors so entry tickets are generally small, around \$1,000, with some funds going as low as a few hundred dollars. At the end of 2018, SCPIs had approximately 750,000 shareholders.²²

22 - EY and ASPIM, 2020, Real estate investment, a force in territorial development: <https://www.aspim.fr/storage/documents/unlisted-real-estate-investment-funds-in-france-ey-5e282a216e5b8.pdf>

2. Institutional Aspects of French Commercial Real Estate Investment Funds

Exhibit 4: Distribution of the commercial SCPI fund population by asset category at the end of 2019



SCPI - Office 37%
SCPI - Diversified 30%
SCPI - Retail 23%
SCPI - Specialised 10%

Notes: The pie chart represents the breakdown by asset category of the population of commercial SCPI funds operating at the end of 2019. The blue, red, green and purple slices respectively represent the number of Office, Diversified, Retail and Specialised SCPIs as a percentage of the total number of commercial SCPI funds.

Source: IEIF database

2.4 Valuation of SCPIs and Real Estate Liquidity Risk

In this section we provide some information relating to the valuation processes used by SCPIs and the role these play in the functioning of their secondary markets. We then provide an introduction to the liquidity risk impacting SCPI investments and conclude with a brief recap of the usual trade-off between listed and non-listed real estate vehicles.

2.4.1 The Valuation and Secondary Market Procedures of SCPI Shares

The valuation of an SCPI and the applicable procedure for investors to acquire or dispose of their shares (through a primary or a secondary market) will vary whether the vehicle is open-end or closed-end.

For open-end SCPIs, genuine secondary market transactions (directly between a buyer and a seller) of shares are rare and very small in size. Most transactions take place on a primary market arranged by the IMC, with investors sending subscription and redemption orders on any given day. Orders are handled on a first-come-first-served basis, and the amount paid or received by investors will be based on a methodology further described below. The IMC will determine and publish an official *subscription price (prix de souscription)*, generally on a quarterly basis. Regulation requires the IMC to set the subscription price within a $\pm 10\%$ band around the *replacement cost* of the fund, which is equal to the Net Asset Value (NAV) of the fund (based on an independent real estate appraisal) plus subscription fees and stamp duties.

Subscription orders will be executed at the subscription price while redemption orders matched by subscription orders will be executed at the subscription price minus subscription fees. Unmatched redemption orders (in case redemptions exceed subscriptions) will only be executed if the SCPI has set aside enough cash and liquid assets, in which case shares shall be redeemed at a price set by the IMC somewhere between NAV and NAV minus 10% (as per the regulation). In the absence of cash and liquid assets, unmatched redemption orders will remain pending.

For closed-end SCPIs, the procedure is somewhat closer to that of a listed vehicle. From time to time the SCPI will seek to raise additional capital and investors will be able to purchase

2. Institutional Aspects of French Commercial Real Estate Investment Funds

newly issued shares on the primary market at a subscription price determined according to the logic prevailing for open-end SCPIs. Outside these subscription periods, the published price reflects actual secondary market transactions organised by the IMC at pre-established dates, usually once or twice a month. The IMC computes a market-clearing *execution price* resulting from supply and demand available on that date and sets the official subscription price equal to the execution price plus a secondary transaction fee and stamp duties. Buyers of shares will pay the subscription price, while sellers will receive the execution price.

2.4.2 Liquidity Risk in the SCPI Market

As detailed in Schoeffler (2020), SCPI investors are not immune to liquidity risk.

First, the assets held by SCPIs – namely commercial real estate properties – are relatively illiquid by nature: physical transaction volumes oscillate between 10 and 15% of the overall universe in normal periods and can drop dramatically in times of market stress. SCPIs will therefore naturally inherit the relatively low liquidity of the commercial real estate asset class. In addition, the corporate structure of SCPIs will largely impact the liquidity risk ultimately borne by SCPI investors.

In closed-end SCPIs, the non-redeemable nature of the fund's liabilities means that liquidity risk is "priced" via an over-the-counter secondary market organised by the IMC. SCPI shares may therefore trade at a discount to the fund's NAV in times of stress when the market price of liquidity is elevated, and investors are keen to monetize their shares. Therefore, although some small

closed-end SCPIs may not trade at times and may report pending orders, there is in principle a selling price at which a potential buyer will be interested to step in.

For open-end SCPIs, liquidity risk results from the structural mismatch between the fund's assets and liabilities and therefore the risk that a redemption request may not be met because the IMC is not able to liquidate enough assets in an orderly fashion in time or is not able to accurately value the assets. This is typically what can happen to open-end funds in a period of market crisis when large redemption requests and investors' need for liquidity tend to compound the effect of declining asset values.

The most recent example is the UK open-end property fund crisis that unfolded in 2020 when the economic fallout from the coronavirus pandemic cast doubt over the value of underlying real estate assets and triggered waves of redemption requests. Back in April 2020 the *Financial Times* reported that at least 10 property funds managing £13bn in assets had suspended redemptions.²³ The suspensions were implemented when property valuation companies declared there was "material uncertainty" over the value of the funds' assets. A liquidity crisis also hit the German open-end real estate funds in 2008–2009 when large redemption requests by shareholders led to some funds suspending the redemption of shares or even going into liquidation. Interestingly, Gerlach and Maurer (2020) show that i) the liquidity crisis coincided with a material increase in the secondary market activity (on German stock exchanges) of the open-end real estate funds subject to a

23 - <https://www.ft.com/content/2a35a372-82f4-4f09-836c-6004bf667f20>

2. Institutional Aspects of French Commercial Real Estate Investment Funds

redemption suspension or under liquidation, ii) secondary market activity of German open-end real estate funds has been increasing overall since the crisis, partly due to the introduction of minimum holding and notice periods, and iii) secondary market activity also tends to increase when funds suspend *subscriptions* due to a lack of investment opportunities.

The SCPI market experienced a liquidity crisis in the early 1990s. Although most SCPIs were closed-end at the time, the regulation at the time (eventually amended in 2002) required the execution price to be based on NAV rather than on a market-clearing price resulting from supply and demand. The prevailing real estate crisis therefore turned into a liquidity crisis for SCPIs with no buyer willing to step in at a price that did not fully reflect market conditions.

Managing liquidity risk is a major concern for managers of open-end SCPIs, who have a number of mitigating measures at their disposal. For instance, the presence of subscription fees effectively assigns a fixed cost to an early exit (like a bid-offer spread) and incentivizes investors to consider a longer-term investment horizon. The manager's +/-10% discretion in determining the fund's subscription and redemption prices may also be part of a liquidity risk management policy. Although this determination is often the result of the IMC's commercial strategy, the valuation procedure is also akin to a swing pricing methodology that can be used to manage the fund's liquidity in times of stress, thus ensuring that the early exit of some investors does not penalize remaining investors.

Schoeffler (2020) provides a historical analysis of the liquidity of SCPI shares as well as a detailed description of the tools used by SCPIs to manage liquidity risk. The latter include notice periods, "gates", side-pockets, or temporary suspension as a last resort. In case of prolonged suspension, the IMC also has the ability to organise a secondary market for the shares, effectively transitioning to a closed-end fund set-up.

Liquidity risk is also a primary concern for European regulators. The *European Securities and Markets Authority* (ESMA) published new "Guidelines on liquidity stress testing in UCITS and AIFs" in September 2019, which naturally apply to SCPIs. The guidelines took effect in September 2020 and will require SCPI managers to conduct stress testing at least annually on the assets and liabilities of the funds they manage, including stressing prospective redemption requests by investors.

2.4.3 The Trade-off Between Liquidity and Correlation with Equity Markets

In practice, SCPI shares trade a lot less than listed REITs shares. Over the 2009–2019 period, the average volume of commercial SCPI shares exchanged each year between buyers and sellers (that is the sum of secondary transactions and matched redemptions for closed-end and open-end SCPIs respectively) amounted to only 1.8% of the overall AUM.²⁴ This compares with a typical annual share turnover of 30% or more for listed REIT vehicles.²⁵ Unlike REIT shareholders, SCPI investors may also, from time to time, be unable to dispose of their SCPI shares. The amount of redemptions pending at year-end was on average 0.2% of the overall universe's AUM

24 - Pierre Papier : <https://www.pierrepapier.fr/>

25 - Schoeffler (2020)

2. Institutional Aspects of French Commercial Real Estate Investment Funds

between 2009–2019 (historical highs of 3.3% and 1.8% of AUM were reached respectively in 1996 and in 2008) but with significant variations at the fund level: unmatched pending redemptions reached 7.9% of AUM in 2018 and 3.5% of AUM in 2019 for individual SCPIs.

The strong liquidity offered by REITs (SIICs in France) comes at a cost to investors however. In return for the ability to dispose of the asset on an exchange at any time, investors must sacrifice, in the short term or in some specific market cycles, the attractive decorrelation of the real estate asset class with equity markets as well as tolerate an increased level of volatility. Put another way, REITs sometimes behave more like equities than real estate, thus undermining the diversification benefits targeted by multi-asset investors. See for example Glascock et al. (2000), Clayton and Mackinnon (2001), or Niskanen and Falkenbach (2010) for academic studies of these correlation effects. More specifically for the French market, Schoeffler (2009) identifies an impact of the investment horizon on the correlation profiles between the performance of direct commercial real estate investing, the performance of French REITs and the performance of the broad equity market: in the short term the returns of French REITs are more correlated with the equity market than with direct real estate investing, while the reverse is true over a 5-year period.

It would therefore seem that investors need to choose between diversification benefits and liquidity since available investment vehicles provide either one or the other, but not both at the same time. However, investors with long-term objectives who neither require on-demand

liquidity nor are sensitive to short-term or cyclical volatility should, all else being equal (e.g. fees), be indifferent toward the choice of real estate vehicle and should be able to circumvent the trade-off entirely. Pension funds happen to fit into this category of long-term investors and the composition of their portfolios seems consistent with the intuition: indeed, the review of global pension funds conducted by Andonov et al. (2013) shows that the more a pension fund invests in the real estate asset class, the more it diversifies between listed and non-listed real estate vehicles.

2. Institutional Aspects of French Commercial Real Estate Investment Funds

3. Dataset and Statistical Treatments

3. Dataset and Statistical Treatments

This second section is entirely dedicated to the SCPI dataset that we analyse in Sections 4, 5 and 6. We first review the data and highlight the estimation challenges it brings about, and then address these via some statistical treatments. Our goal is to mitigate the statistical biases of the data in order to enhance the reliability of our analyses in Sections 4, 5 and 6.

In a nutshell, consistent with the academic literature on real estate investment, we report a smoothing problem with the open-end SCPI return data. Another major issue is the presence of infrequent data, traditionally regarded as a source of estimation biases. We suggest handling both problems by using a combination of desmoothing techniques and trade-to-trade regressions assuming a simple market model. In the end, our procedure leads to a material correction of volatility for open-end SCPIs (an approximate doubling of volatility on average) and no material correction for closed-end SCPIs.

3.1 Dataset Analysed in the Paper

Our statistical analysis relies primarily on a dataset kindly provided by the *Institut de l'Épargne Immobilière et Foncière* (IEIF), the leading independent research organization covering the French real estate investment market. The IEIF dataset included 241 SCPI vehicles and covered the following fund-level data from 1990 to 2019:

- Subscription price (semi-annual frequency between 1990 and 2014, quarterly thereafter)
- Dividend (annual frequency between 1990 and 2014, quarterly thereafter)
- AUM (annual frequency)

- Capital type (annual frequency); note that this field is not static, since some SCPIs converted from closed-end to open-end over the years
- Asset category (annual frequency): Office, Diversified, Retail, Specialised
- Transactional and secondary market data such as subscriptions, matched redemptions, unmatched redemptions, pending orders, and secondary transactions (annual frequency)

The IEIF dataset also included SCPI index-related data from 1980 to 2019, linked to the EDHEC IEIF Commercial Property (France) Index as well as its sub-indices by capital type (open-end and closed-end sub-indices). It included two sets of historical prices for each index, one with dividends reinvested and one without dividends reinvested (that is a *total return* and a *price return* version of each index). Prices for the main EDHEC IEIF Commercial Property (France) Index are available annually from 1980 to 1987, then semi-annually from 1988 to 2008, and monthly thereafter since June 2008. Prices for the sub-indices are available annually from 1980 to 1987, then semi-annually from 1988 to 2014, then quarterly from 2015 to 2016, and monthly thereafter since January 2017. The EDHEC IEIF Commercial Property (France) Index was co-developed by IEIF and EDHEC-Risk Institute (see EDHEC (2009)) and is currently jointly published by IEIF and EDHEC-Risk Institute. Some index data not related to SCPIs was obtained from the IEIF website directly (<https://www.ieif.fr/>) and includes daily price histories (going back to 31 December 2002) of the Euronext IEIF SIIC France Index (representing the universe of French REITs) and the CAC All Tradable Index (representing French listed equities, formerly known as SBF 250 Index).

3. Dataset and Statistical Treatments

We also manually sourced public information on SCPI vehicles from various specialised websites dedicated to individual retail SCPI investors, such as www.pierrepapier.fr, www.meilleurescpi.com, www.primaliance.com, www.myscpi.com and www.immobail.com, which provide access to both processed data and official fund documentation (annual reports, offering documents). This allowed us to enrich our dataset with the following fund-level data as at the end of 2019:

- Number of real estate assets held in the portfolio
- Fees (management fee and subscription fee)
- Portfolio real estate asset class exposures (offices, retail shops, hotels, industrial premises, warehouses, medical centres, etc.)

We then applied several filters to generate a tractable universe of SCPIs with data of sufficient relevance and quality, and with enough history to cover a full real estate cycle of at least 12–15 years.

Our first filter was to exclude data prior to 2003 to reflect the regulatory changes that came into effect in 2002 and 2003 (respectively *Règlement COB 2001-06* and *Décret n° 2003-74 du 28 janvier 2003*) and materially impacted SCPIs in two ways. First, the secondary market of closed-end SCPI shares became exclusively based on supply and demand rather than an appraised NAV, and second, SCPIs were granted additional flexibility in the management of their real estate portfolio (in particular their ability to dispose of some assets or to conduct property improvement and renovation). Finally, we excluded SCPIs that were no longer operating at the end of 2019, and those that were not already operating as at the end of 2003. The resulting dataset comprises 55

commercial SCPIs which had all been operating for at least 16 years.

Our filter may arguably introduce a survivorship bias since our analysis implicitly excludes those SCPIs that were operating in 2003 but not in 2019. We therefore examined the performance of non-survivors and comparable survivors. More specifically, we compared the 36 SCPIs that *stopped* operating between 2003 and 2019 (the "non-survivors") to the dataset of 55 SCPIs we wish to analyse (the "survivors"). We found that non-survivors were generally smaller than survivors, with the former falling into the bottom 3 quartiles of the AUM distribution of the surviving SCPI population. We controlled for the size effect by comparing the population of 36 non-survivors with the population of 39 survivors comprising the bottom 3 AUM quartiles and we found no material bias in terms of capital type (open-end vs closed-end) or asset category (Office, Diversified, Retail, Specialised) distribution. Therefore, we compared the performance of the equally-weighted basket of non-survivors with that of the equally-weighted basket of the 39 "small" survivors between 2003 and 2013 (beyond 2013 the non-surviving basket had fewer than 10 constituents remaining, which we considered too small for our comparison). The average annual total (log-)returns were respectively 9.1% and 10.1% for the non-surviving and surviving baskets. We found the difference in average returns to be statistically non-significant (p -value = 37%) over the 2003–2013 period. In conclusion, although we did observe an economic difference in performance between excluded non-survivors and included survivors, we did not find any statistical evidence of a bias caused by our filter.

3. Dataset and Statistical Treatments

Exhibit 5: Comparison between our dataset and the overall commercial SCPI market at the end of 2019, based on the distribution by asset category, capital type and fund size, and based on secondary market activity

	Dataset	Commercial SCPI Market		Dataset	Commercial SCPI Market
Number of funds	55	97	Total AUM (\$bn)	48.6	68.3
%SCPI - Office	55%	37%	%SCPI - Office	79%	67%
%SCPI - Diversified	22%	30%	%SCPI - Diversified	14%	17%
%SCPI - Retail	22%	23%	%SCPI - Retail	7%	9%
%SCPI - Specialised	2%	10%	%SCPI - Specialised	0.2%	7%
%Open-end	60%	75%	%Open-end	87%	91%
%Closed-end	40%	25%	%Closed-end	13%	9%

Fund size distribution (\$mm)	Dataset	Commercial SCPI Market	Secondary market activity (% of AUM)	Dataset	Commercial SCPI Market
min AUM	9	1	2019	1.94%	1.66%
max AUM	3 985	3 985	2004-2019 average	2.01%	1.93%
average AUM	884	704			
median AUM	435	570			

Notes: The first row in the upper left table compares the number of SCPI funds in our dataset with the number of SCPI funds in the overall commercial SCPI market. The following four rows (respectively the last two rows) compare the breakdown by asset category (respectively by capital type) of the population of SCPI funds in our dataset with the same breakdown of the whole population of commercial SCPI funds.

The first row in the upper right table compares the total AUM of the SCPIs in our dataset with the total AUM of the commercial SCPI market. The following four rows (respectively the last two rows) compare the breakdown by asset category (respectively by capital type) of the total AUM of the SCPIs in our dataset with the same breakdown of the total AUM of the commercial SCPI market. AUMs are expressed in \$bn.

The lower left table compares the minimum, maximum, average and median AUM of the population of SCPIs in our dataset with the minimum, maximum, average and median AUM of the population of commercial SCPIs. AUMs are expressed in \$bn.

The lower right table compares the total volume of secondary market activity of the SCPIs in our dataset (as a percentage of their total AUM) with the total volume of secondary market activity of the commercial SCPI market (as a percentage of its total AUM). The first row reports the 2019 figures, while the second row reports the average of the annual figures from 2004 to 2019.

In an attempt to assess how representative our dataset is, Exhibit 5 presents information about the breakdown (in terms of number of funds or AUM, respectively) into asset categories (Office, Diversified, Retail, Specialised) and capital types (Open-end versus Closed-end) for our dataset and for the commercial SCPI universe as a whole; we also present information, both for our dataset and the commercial SCPI market, related to the fund size distribution and the volume of secondary market activity (relative to AUM). We find that our dataset captures approximately 60% of the 97 SCPI vehicles operating as at the end of 2019

and 70% of their AUM. We also note that the composition of the dataset is representative of the overall SCPI market in terms of asset category and capital type. One notable exception, however, is the under-representation of Specialised vehicles, i.e. SCPIs primarily investing in real estate asset classes that are neither office nor retail, such as logistics, data centres, healthcare or hotels. This is because the majority of Specialised SCPIs were set up in recent years (after 2014), while our filters naturally skew the dataset towards long-established funds. Our dataset nevertheless contains an economic exposure to

3. Dataset and Statistical Treatments

these alternative real estate asset classes via the Diversified SCPI category (12 vehicles out of 55). We also note from Exhibit 5 (see the two lower tables) that the composition of the dataset is representative of the overall commercial SCPI market in terms of fund size and secondary market volumes.

It is worth highlighting that approximately half of the open-end funds in the dataset are actually "converted" SCPIs, which used to operate as closed-end vehicles but decided to amend their capital structure sometime during the 2003–2019 period to accommodate for the large investor inflows into the SCPI universe. Our dataset allows us to distinguish the closed-end and the open-end periods for each of these SCPIs, for the purpose of a more granular analysis. Note that although asset category is in principle a dynamic field (the composition of an SCPI's portfolio of assets may vary over time), in practice no change in asset category was observed during the 2003–2019 period among the 55 SCPIs in our dataset.

3.2 Identifying and Correcting for Biases in SCPI Performance Data

We measure an SCPI's performance through the rate of return of the subscription price as well as the dividend amounts distributed by the SCPI over time. More specifically, for every SCPI we compute price returns, total returns and dividend yields as follows:

$$\begin{aligned} & \textit{Price Return between }]t, t + 1] \\ & = r_{t,t+1} = \ln\left(\frac{P_{t+1}}{P_t}\right) \quad (\text{d1}) \end{aligned}$$

$$\begin{aligned} & \textit{Total Return between }]t, t + 1] \\ & = r_{t,t+1}^D = \ln\left(\frac{P_{t+1} + D_{t,t+1}}{P_t}\right) \quad (\text{d2}) \end{aligned}$$

$$\begin{aligned} & \textit{Dividend Yield between }]t, t + 1] \\ & = y_{t,t+1} = r_{t,t+1}^D - r_{t,t+1} = \ln\left(1 + \frac{D_{t,t+1}}{P_{t+1}}\right) \quad (\text{d3}) \end{aligned}$$

where P_t and $D_{t,t+1}$ are respectively the reported subscription price at time t and the gross dividend amount paid between $]t, t+1]$. More generally, unless otherwise specified in the rest of the paper, returns should always be understood as log-returns.

Note that the risk and return metrics considered in the paper therefore do not account for (fixed) subscription fees. The impact of subscription fees (both in absolute terms and in relative terms in case fees differ from one SCPI to the next) is expected to be largely reduced over the long holding periods applicable to SCPIs. The general recommendation for SCPI investors is indeed to hold their shares for at least 8 years and the average annual turnover observed across the SCPI universe between 1990 and 2019 is less than 2% of outstanding shares, which implies an average effective holding period of several decades. It is also worth noting that competition among SCPIs for capital inflows has over time contributed to a convergence in fee levels: there is relatively little dispersion in the distribution of subscription fees across the commercial SCPI population in 2019, with a median of 10% (see Section 2.3) and approximately 8 SCPIs out of 10 applying a subscription fee of between 8% and 12%. Assuming a hypothetical 20-year holding

3. Dataset and Statistical Treatments

period, a hypothetical 10% subscription fee would imply a return reduction of 0.50% per annum, while a hypothetical 4% difference in subscription fee would imply a difference in return of 0.20% per annum.

An initial observation of the SCPI dataset allows us to detect three potential challenges, all somewhat related to the relative lack of liquidity of SCPIs. First, a number of SCPIs experience long periods of time during which the subscription price moves very little, if at all. This specifically affects the price of open-end SCPIs, with an average realised annual price return volatility during the 2003–2019 period that is 2.8 times lower than for their closed-end counterparts, and even 7.1 times lower during the 2009–2019 sub-period. To put things into perspective, in Exhibit 6 we provide a comparison of historical volatilities for SCPIs versus French REITs and French Equities.

Exhibit 6 leads to several observations. First, French REITs are almost as volatile as French equities despite the fundamental difference in asset class. This is consistent with the equity-like behaviour of listed REITs mentioned in Section 2.4.3. Second, closed-end SCPIs seem to be far less volatile than French REITs (9.0% vs 17.7%)

despite their similarly closed-end capital types and market-based valuation processes. Although more challenging from a data standpoint, a more rigorous comparison would be to use the average volatility of a representative population of French REITs to avoid introducing the effects of index diversification on volatility. One should also adjust for the materially higher levels of leverage used by French REITs compared to SCPIs. Indeed, until recently the loan-to-value (LTV) of SCPIs did not exceed 10% on average while French REITs have operated with an LTV of between 40 and 45% on average since 2010, having reached average levels of 55% in the previous decade.²⁶ For the purpose of our analysis we use an indicative LTV level of 50% and compute “unlevered” volatilities (using Bloomberg data) for those constituents of the Euronext IEIF SIIC France Index that have a price history going back to 2003 (this represents approximately two-thirds (70%) of the prevailing index constituents as at the end of 2020). The estimated average unlevered annual volatility for the 2003–2019 period is equal to 17.0%, still indicating that closed-end SCPIs are materially less volatile than their listed REITs counterparts. We also note that the Retail asset class bias of French REITs (see Section 2.1) cannot explain such a discrepancy, because the average volatility of

Exhibit 6: Comparison between the 2003–2019 volatilities of the SCPIs in our dataset, the 2003–2019 volatility of French REITs and the 2003–2019 volatility of French equities

Asset type	2003–2019 Annual historical volatility of gross total returns
Open-end SCPIs (average)	3.2%
"Converted" open-end SCPIs (average)	7.1%
Closed-end SCPIs (average)	9.0%
French REITs (Euronext IEIF SIIC France Index)	17.7%
French equities (CAC All Tradable Index, formerly SBF 250)	19.8%

Notes: The first (respectively second and third) row reports the equally-weighted average of 2003–2019 total return volatilities of open-end (respectively converted and closed-end) SCPIs in our dataset. The fourth row represents the 2003–2019 total return volatility of the Euronext IEIF SIIC France Index, while the fifth row represents the 2003–2019 total return volatility of the CAC All Tradable Index.

26 - Pierre Papier, Fédération des Sociétés Immobilières et Foncières (FSIF) : <https://fsif.fr/>

3. Dataset and Statistical Treatments

those closed-end SCPIs belonging to the Retail asset category is not materially different from that of the full population of closed-end SCPIs (9.5% vs 9.0%). Our third observation is that the volatility of "converted" open-end SCPIs is somewhere between that of open-end and closed-end SCPIs. More specifically, we observe a dramatic reduction in price return volatility in the years following an SCPI's conversion from closed-end to open-end.

We draw two conclusions from the above observations. First, closed-end SCPIs are not subject to the equity-like behaviour of listed REITs and their volatility is most likely a fair reflection of the economic risk of commercial real estate assets. And second, the low volatility of open-end SCPIs is due to a smoothing effect directly caused by their appraisal-based valuation, which fundamentally differs (see Section 2.4.1) from the market-based valuation of closed-end SCPIs.

In this context, the first challenge is to correct for the smoothing effect and ensure the risk profile of open-end SCPIs is accurately represented in our analysis. Our dataset indicates no significant difference between the underlying asset exposures (Office, Retail, Specialised) of open-end and closed-end SCPIs so we would expect the true (without smoothing) volatility of open-end SCPIs to be more in line with that of closed-end SCPIs. Smoothing is a common and well-documented phenomenon in non-listed real estate performance data, and we address this topic in more detail in Sections 3.3 and 3.4.

The second challenge is somewhat related to the first but is specific to SCPIs and their valuation

procedure. As described in Section 2.4.1, the subscription price of an open-end SCPI is not only based on an appraised NAV but is also subject to a +/-10% discretion granted to the IMC. The amount of discretion available to a manager is therefore of the same order of magnitude as the volatility of the SCPI as an investment vehicle. This is potentially another source of noise in the data that may lead to a misrepresentation of open-end SCPIs' risk profile. The discretionary adjustment is most often a consequence of the commercial strategy of an IMC: lowering the price is a way of attracting more capital and disincentivizing existing investors from redeeming, while increasing the price makes the fund less attractive to new investors generally seeking higher yields. The noise induced by the adjustment is therefore largely unpredictable and very difficult to quantify or model.

We propose to address this issue via an additional layer of data filtering applied to open-end SCPIs, largely inspired by EDHEC (2009) and the principles underpinning the construction of the EDHEC IEIF Commercial Property (France) Index. We first postulate that large and material discretionary adjustments would naturally deter one side of the market, i.e. either buyers or sellers, and would lead to unmatched subscriptions or unmatched redemptions. Conversely, the presence of secondary market activity, i.e. subscriptions matched by redemptions, is the sign that the discretionary adjustment is either not material or at least small enough to keep both buyers and sellers interested. Our proposed filter will therefore be liquidity-based: we only retain prices in a given year when sufficient secondary market activity is observed for the corresponding SCPIs.

3. Dataset and Statistical Treatments

Our threshold is a modified version of the one used to construct the EDHEC IEIF Commercial Property (France) Index. For a given SCPI, we deem the annual secondary market activity to be sufficient if its volume of matched redemptions (or subscriptions) is greater than EUR 2m or if its ratio $\frac{\text{Secondary volume}}{AUM}$ falls into the top two quartiles of the cross-section of the SCPI population.

The absolute threshold is relevant for large-sized SCPIs, while the relative threshold ensures we do not exclude small but actively trading SCPIs from the dataset. The practical implications of the additional filter are detailed in Section 3.4.

The third and final challenge raised by the SCPI dataset is the presence of heterogeneous frequencies of observation. Some portions of the dataset contain quarterly prices while others contain semi-annual data (put another way, we are missing some quarterly prices). Additionally, the liquidity-based filter proposed to address the second challenge creates additional "holes" in the dataset as we voluntarily exclude possibly unreliable prices. While none of these issues affect the computation of SCPI historical returns, they sometimes prevent the estimation of empirical volatilities and correlations via standard statistical techniques. The academic literature has produced solutions for this so-called infrequent data problem which is quite common for less liquid asset classes like hedge funds. We address this matter in more detail in Sections 3.3 and 3.4.

There is to the best of our knowledge no methodology in the academic literature (which we review in Section 3.3) that explicitly addresses both smoothing issues and infrequent data issues

at the same time. In Section 3.4 we propose a framework that combines proven solutions to each individual problem.

3.3 Literature Review of Issues Related to Smoothing and Infrequent Data

A large body of academic research relates to data smoothing issues, so we focus on the strand that directly addresses smoothing linked to appraisal-based real estate valuations.

As presented in Geltner (1991, 1993a) and in Key and Marcato (2007), it is commonly believed amongst academics and practitioners that professional property appraisers tend to "smooth", i.e. they only partially adjust property values over time.

This assumption induces the following relationship between the true market value of a property and its reported appraised value (see Geltner (1991, 1993a) for details):

$$V_t^* = (1 - \alpha)V_t + (1 - \alpha)e_t + \alpha V_{t-1}^*$$

where V_t^* is the reported (appraised) value, V_t is the true value, α is a positive fraction between 0 and 1, and e_t is a random error term that results from the imperfectly observable nature of the real estate market since only transactions pertaining to "comparable" properties can be practically observed.

For a diversified portfolio of real estate assets the observation error is expected to diversify away and the smoothing effect translates into:

$$r_{t,t+1}^* = (1 - \alpha)r_{t,t+1} + \alpha r_{t-1,t}^* \quad (1)$$

3. Dataset and Statistical Treatments

where $r_{t,t+1}^*$ is the reported (appraised) price (log-) return of the portfolio, and $r_{t,t+1}$ is the true price (log-)return.

Not only is it intuitively more comfortable for an appraiser to report small changes in value rather than large ones, but there are also theoretical justifications for this behaviour. Indeed, Quan and Quigley (1991) propose a model for the real estate market and its participants, formalize the property appraiser's problem, and show that smoothing can be an optimal strategy to appraise the value of a property when observing noisy comparable transactions. Noise is represented by the random observation error e_t , and is embedded in comparables' transaction prices because of the real estate market imperfections, such as heterogeneity and fixed nature of the assets, or cost of search and conditions of sale. The model predicts that the larger the variance of e_t , the more smoothing is optimally applied by the appraiser, i.e. the higher the required α .

The practical implication of smoothing on the times series of reported returns is the presence of autocorrelation. Indeed, assuming the true returns ($r_{t,t+1}$) are "unpredictable" (or more formally, if the true returns are independent increments as a result of market efficiency), equation (1) implies that the 1st-order (Lag 1) autocorrelation of the observed returns ($r_{t,t+1}^*$) is equal to α . Therefore, the most common "desmoothing" approach amongst practitioners (see Key and Marcato (2007)) is to first estimate α by computing the empirical autocorrelation and then infer the true returns ($r_{t,t+1}$) by inverting equation (1):

$$r_{t,t+1} = \frac{r_{t,t+1}^* - \alpha r_{t-1,t}^*}{1 - \alpha} \quad (2)$$

Appraisal is not the only source of smoothing described in the real estate literature. Geltner (1993b) analyses the effect of temporal aggregation, typically defined as the use of individual property valuations occurring at different points in time over a period to compute the returns of a portfolio as of a single point in time. Temporal aggregation occurs in real estate because the market is thin, and the usual workaround used by appraisers is to collect transaction data at different points in time. Geltner's (1993b) conclusion is that even if individual property prices were transaction-based rather than appraisal-based (and therefore not subject to smoothing), the presence of temporal aggregation into a portfolio would lead to a smoothing effect because the computed portfolio value would effectively represent an average across time rather than a spot value at a given point in time. The smoothing effect can be detected again via the serial correlation of observed returns. For example, assuming the true portfolio returns are unpredictable and assuming that individual properties are valued at points in time staggered evenly throughout each calculation period, Geltner (1993b) predicts a 1st-order autocorrelation of exactly 25% for the observed (smoothed) portfolio returns.

Key and Marcato (2007) indicate that the industry is aware of this second potential source of smoothing, which is largely visible in real estate indices. The common practice is again to rely on the desmoothing technique presented above, which de facto attempts to correct for both smoothing effects.

3. Dataset and Statistical Treatments

The issue of infrequent data (also known as infrequent trading, non-synchronous trading, or the Fisher effect) is also widely studied in the academic literature.

Fisher (1966) points out that the tendency for share prices published at the end of a given period to represent the last traded price (possibly occurring well ahead of the end of that period) is a source of statistical estimation bias. More specifically, this would cause a stock index constructed from such shares to be implicitly an average of asynchronous prices which would in turn create positive autocorrelation in the index returns. This is often termed the "Fisher effect", not to be confused with its macroeconomic counterpart. It is conceptually very similar to the temporal aggregation effect described earlier, and both effects induce positive index autocorrelation.

Schwert (1977) detects the presence of the Fisher effect while estimating market betas by comparing the results of a standard regression of monthly returns with those of a regression using "trade-to-trade" monthly returns, meaning returns computed from the *last trade* of a given month to the *last trade* of the following month. The trade-to-trade regression is a way of neutralizing the effect of non-synchronous trading. Scholes and Williams (1977) further formalize the issue of non-synchronous trading and how it introduces a problem of errors-in-variables in the standard estimation of stock betas. The solution proposed is a consistent estimator of beta based on the aggregation of the regression coefficients obtained against lagged, matching and leading market returns. Dimson (1979) proposes another method based on the aggregation of regression

coefficients computed against lagged, matching and leading returns. Unlike Scholes and Williams (1977), the new methodology does not require knowledge of trading dates and does not require prices to be preceded or followed by a transaction in an immediately adjacent period.

While estimating stock betas, Marsh (1979) decides to address the infrequent data issue by using the same trade-to-trade method as Schwert (1977) rather than the aggregated coefficient method suggested by Dimson (1979) and Scholes and Williams (1977). The first reason cited is that the market indices (the independent variables) are not materially (if at all) subject to infrequent trading, only the stocks (the dependent variables) are, and that actual trade dates and trading prices are known for both the index and the stocks. These are effectively necessary (and simplifying) conditions, which Dimson (1979) also mentions, without which the trade-to-trade method (conceptually simpler than the aggregated coefficient method) cannot be implemented. The other reason indicated by Marsh (1979) is that the trade-to-trade method can be fitted into the paper's broader computations.

Asness et al. (2001) apply the aggregated coefficient techniques introduced by Scholes and Williams (1977) and Dimson (1979) to estimate the unbiased beta of hedge fund returns to the S&P 500 index, arguing that published hedge fund returns are affected by infrequent trading of their underlying assets (leading to stale valuations) and by managed pricing. Finally, we should add that the academic literature also mentions another much simpler solution (see Dimson (1979) and Asness et al. (2001)) which involves increasing

3. Dataset and Statistical Treatments

the length of the differencing interval to reduce the impact of estimation errors in the presence of infrequent trading. The obvious drawback of this approach is the loss of data points and the natural estimation errors that could result from it, potentially “making the cure worse than the disease”.

3.4 Statistical Treatments Applied to the SCPI Dataset

When putting the challenges observed in our dataset (see Section 3.2) in the context of the conceptual and practical issues described in the literature, we conclude there are four data problems we need to address to be able to estimate accurate SCPI risk parameters which will in turn be used in the remainder of the paper.

The first problem is the appraisal-based valuation of real estate assets held by SCPIs, leading to smoothing as explained in Geltner (1993a). The smoothing is captured through the serial correlation of SCPI returns (where each SCPI is considered a diversified portfolio of real estate assets) and we intend to correct it using the standard desmoothing technique summarised in equation (2).

The second problem is temporal aggregation, as described in Geltner (1993b), which is inherently part of the valuation procedure of individual SCPIs, since each one can be seen as a portfolio of real estate assets. This again leads to smoothing and positive autocorrelation of SCPI returns, which we address via the standard desmoothing technique.

The third problem is the +/-10% discretion granted to IMCs, a form of managed pricing issue. As mentioned in Section 3.2, we use a liquidity-based data filter to overcome the problem.

The fourth and final problem is the presence of heterogeneous frequencies and the additional “holes” created by the liquidity-based filter at various places in our dataset of quarterly SCPI prices. This issue is a form of infrequent trading *at the SCPI level* and not at the *real estate assets* level. We therefore distinguish our smoothing issue from our infrequent data issue and address the two as incremental but not overlapping problems. More precisely, in the hypothetical absence of any infrequent data problem (i.e. if we had liquid quarterly prices for all SCPIs for every period), we assume that applying the standard desmoothing technique to SCPIs' published returns would in principle lead us to a reasonable estimate of their true market returns (whose risk parameters we intend to use in Sections 4, 5 and 6).

We choose to address our infrequent data problem using the method presented in Schwert (1977) and Marsh (1979), by regressing individual SCPI trade-to-trade returns against the associated date-matched returns of a carefully chosen SCPI index (see details in Section 3.4.1) and by inferring each SCPI's risk profile from its regression beta.

We opt for the trade-to-trade method for the same reasons as Marsh (1979): our benchmark SCPI indices are not subject to infrequent trading, we have knowledge of the actual trade dates and trade prices for every SCPI, and we find the

3. Dataset and Statistical Treatments

trade-to-trade method easy to combine with the desmoothing technique described earlier (see details in Section 3.4.4).

In the next section, we present an implementation framework addressing the four data problems we have just discussed.

As mentioned in Section 3.1, our dataset includes 55 SCPIs. There are 43 dates for which some price and dividend information is available, from December 2003 to December 2019. The dates are all quarter-ends, although not every quarter in the 16-year period (64 quarters in theory) is available. Also, some quarterly information is available for some but not all SCPIs.

We have access to 2,341 datapoints out of a theoretically fully complete quarterly dataset of 3,520 datapoints ($3,520 = 64 \text{ quarters} \times 55 \text{ SCPIs}$). After applying the liquidity-based filter described in Section 3.2, the number of points drops to 2,176, which represents 62% of the full theoretical figure. Note that as a result of the liquidity-based filter, we removed two SCPIs from our dataset entirely because their remaining number of "liquid" prices was too small to be analysed.

Another way to describe the infrequent data issue is to say that a large portion (38%) of our dataset is comprised of stale prices. Additionally, as per Section 3.2, we suspect that prices of open-end SCPIs are subject to smoothing. Our goal is to be in a position to compute the historical volatility of any portfolio constructed using one or several of the remaining 53 SCPIs of our dataset, while avoiding the biases that

infrequent data (staleness) and smoothing effects will inevitably cause if empirical variance and covariance estimators are used.

We proceed in four steps. First, we introduce SCPI sub-indices. Then, we estimate the amount of smoothing embedded in the performance of open-end SCPIs, link our empirical findings to the regulatory context of SCPIs, and apply the desmoothing technique to the relevant SCPI benchmark indices. The third step is to present the trade-to-trade regression method to adjust for infrequent data in a simplified setting where smoothing is not considered. Our fourth and final step is to present a combined framework addressing both smoothing and infrequent data. We briefly discuss the numerical implementation and results at the end of Section 3.

3.4.1 Introducing SCPI Sub-Indices

The EDHEC IEIF Commercial Property (France) Index is the only investable SCPI index publicly available and is therefore a natural choice when looking for a benchmark representing the overall SCPI market. However, the index comprises both open-end and closed-end SCPIs (as one would expect), making its performance only *partially* subject to smoothing. The statistical properties of the index (in particular its volatility) are therefore not comparable to those of either an open-end or closed-end SCPI.

For this reason, we consider two sub-indices of the EDHEC IEIF Commercial Property (France) Index that are calculated internally for research purposes using the same methodology but are not available publicly, respectively the sub-index exclusively comprising open-end SCPIs (the "Open-end SCPI

3. Dataset and Statistical Treatments

Index") and the sub-index exclusively comprising closed-end SCPIs (the "Closed-end SCPI Index").

We naturally expect the Open-end SCPI Index to be subject to smoothing effects and therefore be an appropriate benchmark index to analyse open-end SCPIs. Conversely, the Closed-end SCPI Index is an appropriate benchmark for closed-end SCPIs and is expected to be immune to smoothing.

The case of SCPIs that have converted from closed-end to open-end ("converted SCPIs") is interesting in that regard. We expect their performance to be smoothed after their conversion, but not before, and it is likely neither sub-index is an appropriate benchmark for their statistical behaviour. Therefore, we construct a series of customised benchmark indices ("Blended SCPI Indices") that mimic the performance of the Closed-end SCPI Index up to a certain date and then "switch" to

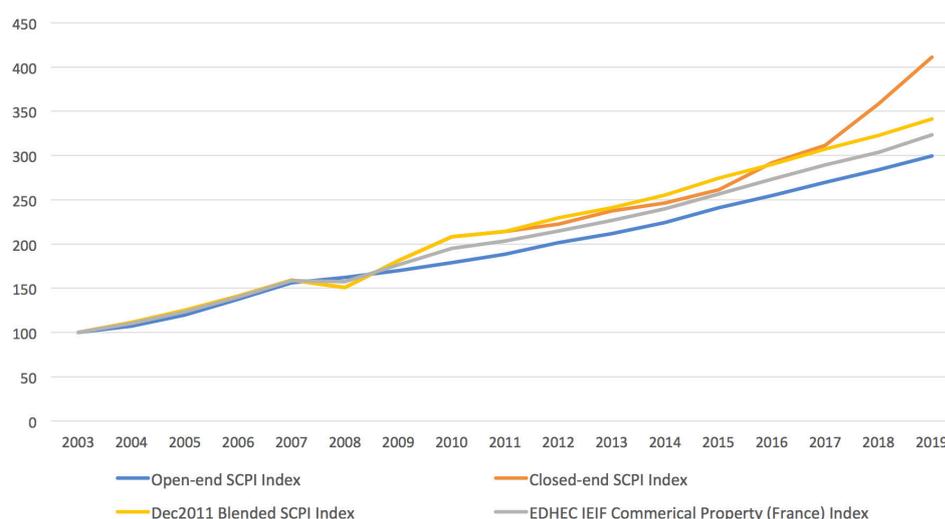
the Open-end SCPI Index. There is potentially one Blended SCPI Index for every converted SCPI, since the capital type conversion date is potentially different for each converted SCPI. The Open-end SCPI Index and the Closed-end SCPI Index can in fact be seen as special cases of the Blended SCPI Indices, where the conversion respectively occurs at the very beginning and the very end of the 2003–2019 period.

Exhibit 7 shows one example of an SCPI Blended Index, namely the Dec2011 Blended SCPI Index. By definition, it mimics the performance of the Closed-end SCPI Index until December 2011, and then mimics that of the Open-end SCPI Index in subsequent periods.

3.4.2 Desmoothing Open-End SCPI Data

Academic research has established links between smoothing effects and the appraisal-based

Exhibit 7: Total return performance of various SCPI indices from 2003 to 2019



Notes: Each index is rebased at 100 as of 31 December 2003 and grows at the total return rate (see definition in Section 3.2). The solid blue (respectively solid red, solid yellow and dashed grey) line represents the evolution of the Open-end SCPI Index (respectively the Closed-end SCPI Index, the Dec2011 Blended SCPI Index and the EDHEC IEIF Commercial Property (France) Index) from 2003 to 2019. The Dec2011 Blended SCPI Index (provided as an example among Blended SCPI Indices) tracks the performance of the Closed-end SCPI Index until December 2011 and tracks the performance of the Open-end SCPI Index in subsequent periods.

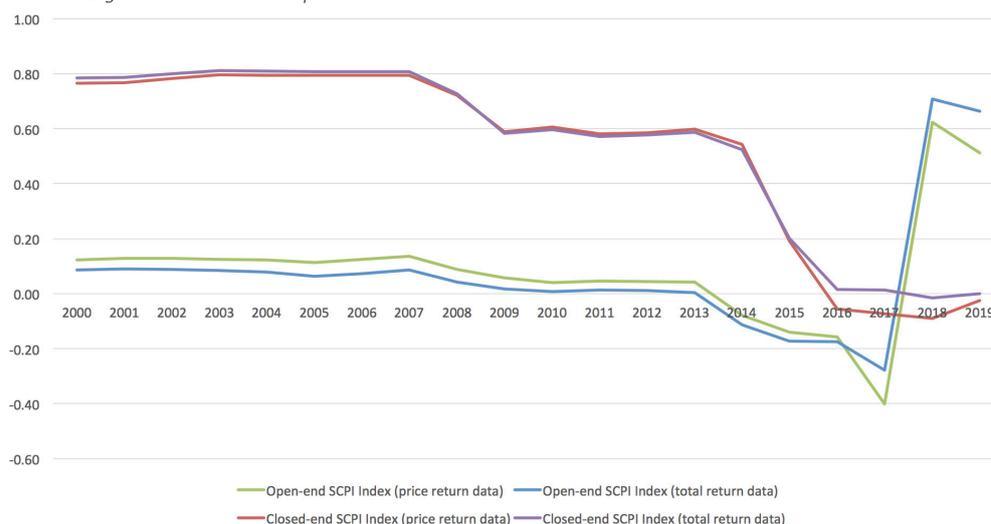
3. Dataset and Statistical Treatments

valuation of property assets. One would therefore naturally expect to observe and measure smoothing via price return data, because it represents capital appreciation, and in turn apply desmoothing techniques to the very same data. However, Key and Marcato (2007) explain that little statistical difference has been observed in practice between total return and price return data associated with real estate assets, and their survey of UK property investment practitioners indicates that desmoothing is often directly conducted on total returns. The two main benefits of directly manipulating total returns are simplified calculations and not having to accurately estimate income return to reconstitute total returns. This is particularly true for SCPI performance data: SCPIs are not subject to regulatory distribution obligations (unlike REITs) and can decide, for commercial reasons, to pay a dividend that deviates from the actual rental income collected during the corresponding year.

For example, when rental income is higher initially than expected, or when capital gains have been realized, the IMC may decide to set aside a reserve that can be depleted in future years, in case rental income unexpectedly decreases. This makes the exact distinction between SCPI income and SCPI capital growth subject to caution.

Geltner (1991) and Geltner (1993b) also observe that smoothing effects, quantified through serial correlation, are not materially different in price return and total return of real estate investments, noting that *"while income is very important in determining the mean return over time, it has a very minor effect in determining the second moments of returns time series"* and that *"income returns are relatively constant over time, so that the volatility and stochastic characteristics of the appreciation returns series closely resemble those of the total returns"*.

Exhibit 8: Evolution of Lag 1 autocorrelation of Open-end and Closed SCPI Indices over time



Notes: Lag 1 autocorrelation is computed using rolling 20-year windows and annual (log-)returns. The x-axis shows the end of each 20-year window (the data is available from 1980). The green and blue lines represent the Open-end SCPI Index's autocorrelation using price and total returns respectively. The red and purple lines represent the Closed-end SCPI Index's autocorrelation using price and total returns respectively.

3. Dataset and Statistical Treatments

The SCPI performance data is consistent with the above observations: for both the Open-end and Closed-end SCPI Indices, the serial correlations observed in *annual* price return and total return track each other closely over time, as indicated in Exhibit 8.

Therefore, all the statistical treatments below relating to smoothing effects are conducted on SCPI total returns. Total returns are also used in trade-to-trade regressions for consistency.

We argue that the Open-end and Closed-end SCPI Indices carry substantially the same amount of smoothing (if any) as their SCPI constituents. Indeed, we consider the two common sources of smoothing, namely appraisal-based valuations and temporal aggregation (see Geltner (1993a) and Geltner (1993b)), to be happening primarily "within" each SCPI, which in practice behaves like a diversified real estate index or portfolio. Specifically, we argue that the construction of the Open-end and Closed-end SCPI Indices (each, effectively, an "index of real estate indices") does not introduce any further material smoothing effect beyond what is already embedded in the SCPI constituents. Indeed, there is obviously no appraisal involved in the index calculation since individual SCPI prices are already known. Additionally, the SCPI prices feeding each index at any point in time are, by construction, subject to little staleness (the cause of temporal aggregation) because the index rules specifically filter out SCPIs that do not have sufficient secondary market activity (see EDHEC (2009)). The reason why staleness cannot be theoretically fully eliminated is because the index rules are by nature backward-looking and assume some persistence in liquidity

(an SCPI that has been liquid in the past year is likely to remain liquid in the coming year). Notwithstanding the notable exception of the SCPI crisis in the early 1990s (see Section 2.4.2), the historical stability of SCPI secondary market volumes as a percentage of their AUM (typically 1.5–2.0% of AUM) indicates that material changes in liquidity (if any) have only affected a few SCPIs and not broad indices.

Consequently, we can infer the smoothing affecting SCPIs' performance data by analysing the autocorrelation of the two SCPI sub-indices displayed in Exhibit 8. This is practically useful because, unlike individual SCPIs, the sub-indices are not subject to infrequent data and their statistical properties (e.g. autocorrelation) can be empirically calculated without suffering from material estimation bias. An interesting story seems to emerge from Exhibit 8 and the evolution of autocorrelation over time. Closed-end SCPIs apparently went from being heavily smoothed to not smoothed at all, while open-end SCPIs did somewhat the opposite. This happens to be consistent with the regulatory and market changes that have affected SCPIs for the past 20 years. Before 2002, most SCPIs were closed-end funds (54% of SCPIs' AUM was in closed-end funds in 2000) and their valuation was tied to appraisal-based NAV. The new regulation imposed a market-based valuation, which effectively made the smoothing vanish. At the same time, the large inflows of investor capital in SCPIs since 2000 incentivised a lot of funds to convert from closed-end to open-end to capture the wave of AUM growth. So it appears that formerly closed-end funds, which were smoothing prices before 2002, have now become open-end funds (only

3. Dataset and Statistical Treatments

9% of SCPI's AUM was left in closed-end funds in 2019) and are driving the recent smoothing effect observed in the Open-end SCPI Index. The relative lack of smoothing observed amongst open-end funds before 2002 may be explained by the relationship between smoothing and capital inflows. An IMC has a strong commercial incentive to smooth returns when there is a large inflow of investor capital to capture, a situation that has typically been prevailing between 2002 and 2019 (with the natural exception of the 2008–2009 period affected by the global financial crisis). Prior to 2002, open-end SCPIs were not as popular as they are today, and "flagship" funds that attracted the majority of new capital back then were mostly closed-end, so the incentive to smooth was presumably not material for open-end SCPIs. A size effect could also be at play: open-end SCPIs held smaller portfolios of assets and were therefore less subject to temporal aggregation, the other common source of smoothing. These contextual elements reassure us that the recent levels of autocorrelation respectively observed for open-end and closed-end SCPIs are grounded in some economic and institutional reality.

The Lag 1 autocorrelation of closed-end SCPIs' annual total returns estimated over the 2003–2019 period is -14%. The figure is not statistically significant (p-value = 62%), which is consistent with the market-based valuation of closed-end SCPIs.

The Lag 1 autocorrelation of open-end SCPIs' annual total returns estimated over the 2003–2019 period is 57%. The figure is statistically significant (p-value = 2.61%) and implies there is a material smoothing effect for open-end SCPIs. Our estimate

of α (see equation (1)) is slightly higher than the "rational or optimal" level of 50% suggested by Geltner (1993a) but we note that embedded in our figure is also the effect of temporal aggregation which naturally increases smoothing.

Also, applying the desmoothing technique (see equation (2) in Section 3.3) to the Open-end SCPI Index total returns series yields consistent results. Before desmoothing, the annualised historical volatility of the index over the 2003–2019 period is 2.99%, which is materially lower than that of the Closed-end SCPI Index (5.86%). After desmoothing, the Open-end SCPI Index's volatility is equal to 5.46% and is somewhat in line with its closed-end counterpart. The ratio of desmoothed volatility over observed volatility is $5.46\%/2.99\% = 1.8$. This is comparable to the ratio of 1.7 estimated by Key and Marcato (2007) for the UK non-listed real estate funds specialised in Office properties.

Therefore, going forward, we use a value of $\alpha = 57\%$ to desmooth all returns related to open-end SCPIs, and apply no desmoothing to returns related to closed-end SCPIs. In particular, the desmoothed version of the Blended SCPI Indices (introduced in Section 3.4.1) are constructed using the desmoothed returns of the Open-end SCPI Index and the native (non-desmoothed) returns of the Closed-end SCPI Index.

In a recent study, Delfim and Hoesli (2021) observe that common desmoothing techniques such as the one used in Sections 3.3 may sometimes generate extreme returns and distort risk measurement. Their paper introduces a robust filter to prevent

3. Dataset and Statistical Treatments

the occurrence of extreme values and ensure the characteristics of (appraisal-based) desmoothed series are akin to those of transaction-based series. We therefore performed a sanity check on the desmoothed returns of the Open-end SCPI Index and did not find any evidence of extreme returns. More specifically, the largest absolute desmoothed annual total returns over the 2003–2019 period (+17.9% and -6.4% respectively) were comparable to the largest absolute annual total returns observed for the (transaction-based) Closed-end SCPI Index (+18.4% and -5.4% respectively).

3.4.3 The Trade-to-Trade Regression Method to Tackle Infrequent Data

In this section we voluntarily depart from the implementation of trade-to-trade regression described in Marsh (1979), in order to adopt a more general presentation. This later (in Section 3.4.4) allows us to incorporate the desmoothing technique into the same framework seamlessly.

We start from a standard linear regression market model describing the behaviour of an individual SCPI's total returns:

$$r_{t-1,t} = a + bR_{t-1,t} + \varepsilon_t \quad (3)$$

where

a and b are constant numbers,

$t = 1, \dots, n$ (there are n equally-sized observation periods and $n+1$ dates and prices),

$r_{t-1,t}$ is the (log-) total return of the individual SCPI between $]t-1, t]$,

$R_{t-1,t}$ is (log-) total return of an SCPI benchmark index over the same period,

and ε_t is a residual error term, such that (ε_t) are assumed to be uncorrelated variables with zero mean and constant variance σ^2 (the latter are often called the Gauss Markov assumptions).

The returns in equation (3) are assumed to be the *true* economic returns (see Section 3.3), meaning the returns we would observe in the absence of smoothing effects. The benchmark index can be the Open-end SCPI Index, the Closed-end SCPI Index or one of the Blended SCPI Indices depending on the nature of the SCPI analysed.

Equation (3) can also be written in a matrix format:

$$r = a\mathbf{1} + bR + \varepsilon \quad (3')$$

where

r, R, ε are $(n \times 1)$ column vectors,

$\mathbf{1}$ is a vector of ones,

and $Var(\varepsilon) = (Cov(\varepsilon_s, \varepsilon_t))_{s,t}$ the variance-covariance matrix of ε is, per the Gauss Markov assumptions, diagonal and equal to $\sigma^2 I_n$, where I_n is the $(n \times n)$ identity matrix.

We now assume we have an infrequent data problem, and only a specific subset of $p+1$ trading dates (t_i) are observable.

The trade-to-trade returns can be derived from equation (3) by summing the 1-period returns between each pair of trading dates t_{i-1} and t_i :

$$r_{t_{i-1},t_i} = (t_i - t_{i-1})a + bR_{t_{i-1},t_i} + v_{t_{i-1},t_i} \quad (4)$$

where

$$v_{t_{i-1},t_i} = \sum_{t_{i-1} < t \leq t_i} \varepsilon_t$$

$i = 1, \dots, p < n,$
and $t_0 = 0 < t_1 < \dots < t_p = n.$

In order to re-write equation (4) in a matrix format, we define the $(p \times n)$ "transfer matrix" F (effectively a matrix representation of the subset of observable trading dates) such that the first row starts with exactly t_1 instances of *one* (1) and

3. Dataset and Statistical Treatments

is comprised of zeroes otherwise, and such that each subsequent row i ($i=2, \dots, p$) is populated with exactly $(t_i - t_{i-1})$ instances of one (1) positioned between column t_{i-1} (not inclusive) and column t_i (inclusive).

Equation (4) is then re-expressed as:

$$F \cdot r = aF \cdot \mathbf{1} + bF \cdot R + F \cdot \varepsilon \quad (4')$$

or in expanded form

$$\begin{pmatrix} r_{t_0, t_1} \\ \vdots \\ r_{t_{p-1}, t_p} \end{pmatrix} = a \begin{pmatrix} t_1 - t_0 \\ \vdots \\ t_p - t_{p-1} \end{pmatrix} + b \begin{pmatrix} R_{t_0, t_1} \\ \vdots \\ R_{t_{p-1}, t_p} \end{pmatrix} + \begin{pmatrix} v_{t_0, t_1} \\ \vdots \\ v_{t_{p-1}, t_p} \end{pmatrix} \quad (4')$$

Equation (4) is a new linear model involving observable returns $F \cdot r$ and $F \cdot R$, and can therefore be used to estimate parameters a and b in order to indirectly solve our initial linear model defined by equation (3). We note that the new residual variable $F \cdot \varepsilon$ no longer satisfies Gauss-Markov assumptions but does satisfy the "generalised" Gauss Markov assumptions since the variance-covariance matrix $\text{Var}(F \cdot \varepsilon) = F \cdot \text{Var}(\varepsilon) \cdot F^t = \sigma^2 F \cdot F^t$ is a known symmetric positive definite matrix.

The *generalised least squares* (GLS) method can be used to solve for a and b . This requires computing the "inverse square root matrix" of $\text{Var}(F \cdot \varepsilon)$ and transforming the linear model of equation (4) into yet another linear model that does satisfy the Gauss Markov assumptions again and can be solved using an ordinary least squares technique (see Amemiya (1985) for a formal presentation of the method).

One important point to note is that implementing the GLS method also allows us to estimate σ^2 via

the sample of transformed residual terms. This means that provided we know the variance of the benchmark index returns R , the trade-to-trade regression method outlined in this section allows us to determine the variance of each individual SCPI's returns. The benefit of this approach is to avoid having to compute a (biased) sample variance estimator on a dataset subject to infrequent trading.

Moreover, if we further assume no correlation between the portions of SCPIs' performance unexplained by benchmark indices (i.e. residual returns (ε_t^i) and (ε_t^j) associated with two SCPIs i and j are uncorrelated; this is a material modelling assumption as we will see below and in Section 3.4.5.), the trade-to-trade regression method applied to our simple market model also provides us with the correlations between SCPIs' returns. This is a model-based correlation matrix estimation method extensively used in the so-called *shrinkage* literature. It is applied in situations where the number of assets is of the same order of magnitude as the number of historical returns available and where the usual sample correlation matrix estimator is therefore subject to large estimation errors. The model-based correlation matrix (also called *structured* estimator) is highly specified and contains little estimation error but is naturally at risk of being misspecified and therefore severely biased. The shrinkage methods (see Ledoit and Wolf (2003 and 2004)) use a weighted average of both estimators to strike a balance between the estimation bias of the structured estimator and the estimation errors of the sample correlation matrix. Our SCPI dataset seems like a good candidate for a shrinkage-based correlation estimation since the

3. Dataset and Statistical Treatments

number of historical returns available is not large compared to the number of assets. Computing a 2003–2019 sample correlation matrix for the 53 SCPIs requires estimating 1,378 parameters based on potentially only 3,392 data points (64 quarterly returns), which seems problematic. However, the additional challenge we face with SCPIs is the presence of smoothing and infrequent data effects, which not only leave us with fewer data points (2,176 instead of 3,392), thus exacerbating the estimation errors, but also create estimation *biases* in the standard sample covariance matrix itself. More recent academic research has considered relaxing the assumptions on which the shrinkage approach relies. For instance, Sancetta (2008) or Bartz and Müller (2014) allow for autocorrelation in returns. Although worthy of future research, the design of a covariance estimation technique addressing all the data challenges raised by SCPIs is beyond the scope of our study. For the purpose of our analysis we will use the structured estimator based on our simple market model, while paying close attention to the statistical significance of the model in order to somewhat control for misspecification risk.

3.4.4 Trade-to-trade Regression Applied to Smoothed SCPI Data

The desmoothing technique envisaged in Section 3.4.2 can be combined with the handling of infrequent data presented in Section 3.4.3 by noting that equation (1) has a simple matrix representation provided we assume $r_{0,1}^* = r_{0,1}$:

$$r^* = M_\alpha \cdot r \tag{1'}$$

where M_α is the following non-singular (assuming $\alpha < 1$) lower triangular ($n \times n$) matrix:

$$M_\alpha = \begin{pmatrix} 1 & 0 & \dots & \dots & 0 \\ \alpha & 1 - \alpha & 0 & \dots & \vdots \\ \alpha^2 & \alpha(1 - \alpha) & 1 - \alpha & \dots & \vdots \\ \vdots & \vdots & \vdots & \dots & \vdots \\ \vdots & \vdots & \vdots & \dots & 0 \\ \alpha^{n-1} & \alpha^{n-2}(1 - \alpha) & \dots & \dots & \dots & 1 - \alpha \end{pmatrix}$$

We follow the same steps and notations as in Section 3.4.3, using the matrix representations of the trade-to-trade regression method and the desmoothing technique. We transform equation (3') by multiplying it subsequently by the "smoothing matrix" M_α and then by the "transfer matrix" F . Acknowledging that $M_\alpha \cdot \mathbf{1} = \mathbf{1}$, we obtain:

$$F r^* = a F \cdot \mathbf{1} + b F \cdot R^* + F M_\alpha \cdot \varepsilon \tag{5''}$$

or in partially expanded form:

$$\begin{pmatrix} r_{t_0, t_1}^* \\ \vdots \\ r_{t_{p-1}, t_p}^* \end{pmatrix} = a \begin{pmatrix} t_1 - t_0 \\ \vdots \\ t_{p-1} - t_p \end{pmatrix} + b \begin{pmatrix} R_{t_0, t_1}^* \\ \vdots \\ R_{t_{p-1}, t_p}^* \end{pmatrix} + F M_\alpha \cdot \varepsilon \tag{5'}$$

Equation (5') is again a linear model involving observable and smoothed returns r_{t_{i-1}, t_i}^* and R_{t_{i-1}, t_i}^* . We use the same GLS method to solve for a and b since $Var(F M_\alpha \cdot \varepsilon) = \sigma^2 F M_\alpha M_\alpha^t F^t$ is a known symmetric positive definite matrix. Just like in Section 3.4.3, the trade-to-trade regression approach leads us to an estimation of σ^2 and in turn to an estimation of the variances and covariances of individual SCPIs' returns.

3.4.5 Brief Review of Numerical Implementation and Results

We run a GLS regression for each of the 53 SCPIs of our dataset, where the inverse square root matrix of $Var(F M_\alpha \cdot \varepsilon)$ is computed using

3. Dataset and Statistical Treatments

a Cholesky decomposition. Two nuances are introduced in the numerical implementation although these do not conceptually change the methodology presented in Section 3 so far.

First, the statistically significant autocorrelation of 57% estimated in Section 3.4.2 relates to annual returns, while our dataset's default price frequency is quarterly. Quarterly and semi-annual Lag 1 autocorrelations were reviewed too but none were statistically significant. As a result, the smoothing matrix M_α is adapted to reflect a Lag 4 autocorrelation in the context of quarterly returns.

Secondly, converted SCPIs need special treatment because their smoothing only starts after their conversion date. This requires a further customisation of their smoothing matrix: the customised matrix is effectively a diagonal block concatenation of an identity matrix (pre-conversion, a converted SCPI is closed-end and not subject to smoothing) and a standard M_α smoothing matrix.

The regression results vary qualitatively across the dataset. The "beta", i.e. the estimated slope coefficient b , is only statistically significant in approximately half the cases (27 SCPIs out of 53), indicating that a "market" model is not always appropriate to explain an SCPI's risk profile. This is consistent with the widely accepted idea that real estate funds carry a lot more idiosyncratic risk than equities or bonds.

The capital type does seem to have an impact in this respect: 73% of the open-end SCPIs analysed had a significant slope coefficient, compared

to only 41% of the closed-end and 44% of the converted SCPIs. Our explanation is linked to a size and diversification effect. Closed-end SCPIs are generally smaller in size than their open-end counterparts: the average closed-end SCPI of our dataset was about 3.5 times smaller (in AUM) than the average open-end SCPI throughout the 2003–2019 period. This is hardly surprising since open-end SCPIs are designed to attract more capital. As a result, we expect closed-end SCPIs to be less diversified (since real estate is a largely indivisible asset class) and bear a larger share of idiosyncratic risk that cannot be explained by a simple market model. The number of assets held (a more rigorous measure of diversification) prevailing at the end of 2019 seems to confirm our intuition: open-end SCPIs held on average 239 assets, while converted SCPIs held 121 and closed-end SCPIs held 71 on average in their portfolio.

The relative lack of predictive power of our simple market model should only impact the (model-dependent) split between systematic and idiosyncratic variance of an SCPI's returns, without impacting the total variance of returns. We find the average total volatility estimates obtained via the GLS regressions to be consistent with intuition. The average (annualised) volatility of open-end SCPIs roughly doubles as a result of our statistical treatments, going from 3.2% to 6.5%, while the average volatility of converted SCPIs increases by about a third, going from 7.1% to 9.5%. The average volatility of closed-end SCPIs changes moderately, from 9.0% to 9.2%, because the corresponding data is not subject to smoothing and because the infrequent trading issues are fairly limited for closed-end SCPIs.

3. Dataset and Statistical Treatments

Turning to Sharpe ratios, our statistical treatments contribute to the alignment of the 3 groups of SCPIs. The (ex-post) Sharpe ratios²⁷ of open-end, converted and closed-end SCPIs go respectively from 1.5, 1.0 and 0.8 to 0.7, 0.8 and 0.8 after our combination of desmoothing and trade-to-trade regression. Note that in this paper we use the Sharpe ratio as a tool to compare risk-adjusted returns of SCPIs or SCPI portfolios. We would not advocate comparing the Sharpe ratio of SCPIs (or SCPI portfolios) with that of other asset classes without accounting for the specific features of real estate investments (see Cheng et al. (2008) for further details on the real estate risk premium puzzle and a modified version of the Sharpe ratio suited for real estate investments).

Unlike for variance estimates, we expect our covariance estimates to be model-dependent and subject to the misspecification risk (a potential source of estimation bias) mentioned in Section 3.4.3. The statistical significance of the market model should influence the covariance estimates because the model only allows co-dependency through the systematic risk component. So our model is expected to under-estimate those correlations for SCPIs with a non-significant "beta" to the benchmark index. For this reason, we rely primarily on the subset of SCPIs for which the slope coefficient b is statistically significant,

and "extrapolate" the estimated correlations to the rest of the population while maintaining a segmentation by capital type. Our estimates of average pairwise correlation within and across the 3 capital groups (open-end, converted and closed-end) are presented in Exhibit 9.

We conclude this section with a few comments on calculation conventions and how we use our processed data in the subsequent Sections 4, 5 and 6.

The statistical treatments described in Section 3 are designed to improve the estimation of second-order moments of SCPI total returns and are not meant to affect sample average returns. Consequently, average total returns are computed using unprocessed data in Sections 4, 5 and 6. Similarly, Sharpe ratios are computed using unprocessed average returns and processed standard deviation of returns.

Although we have used total returns throughout Section 3 to address smoothing and infrequent data issues, we sometimes need (in Sections 4 and 6) to distinguish between total return, price return and dividend yield for descriptive purposes and we therefore wish to clarify some working assumptions here. Sample averages of price returns or dividend yields are computed using

Exhibit 9: Estimated average pairwise correlations segmented by capital type

Average pairwise correlations	Open-end SCPIs	Converted SCPIs	Closed-end SCPIs
Open-end SCPIs	44%	24%	19%
Converted SCPIs	24%	33%	29%
Closed-end SCPIs	19%	29%	36%

Notes: The estimates are obtained from the subset of SCPIs for which "market betas" (computed using 2003–2019 total returns) are statistically significant and meaningful correlation estimates are therefore available. We then apply these average correlations to all other SCPIs in the dataset, in accordance with their capital type.

27 - *Ex post Sharpe ratio* = $\frac{\text{Average Annual LogReturn} - \text{RiskFree Rate}}{\text{Std Deviation of Annual LogReturn}}$, where we use the average of the 10y French OAT yield over the 2003–2019 period (2.52%) as the Risk-Free Rate.

3. Dataset and Statistical Treatments

unprocessed data, consistent with the comment made above about total returns. Dividend yield and price return data are subject to the same infrequent trading issues as total returns data, but to simplify matters we neglect the impact of infrequent data in the estimation of dividend yield volatilities and price return volatilities and only consider the potential impact of smoothing. We view this approximation as acceptable because the second order moments of price returns and dividend yields are solely used for illustrative purposes. As far as the smoothing impact is concerned, because we have assumed that smoothing effects are identical for total returns and price returns (see Section 3.4.2), the same holds true mechanically for dividend yields and the usual desmoothing technique can be used with the same value of α :

$$y_{t,t+1} = \frac{y_{t,t+1}^* - \alpha y_{t-1,t}^*}{1 - \alpha}$$

where $y_{t,t+1}^*$ is the reported (observable) yield, and $y_{t,t+1}$ is the true economic yield.

4. SCPI Risk and Performance Analysis

4. SCPI Risk and Performance Analysis

This section provides some descriptive statistics of our universe of 53 SCPIs. In particular, we look at cross-sectional differences in risk and performance indicators to establish whether such differences are material, which has obvious implications for selection and allocation decisions.

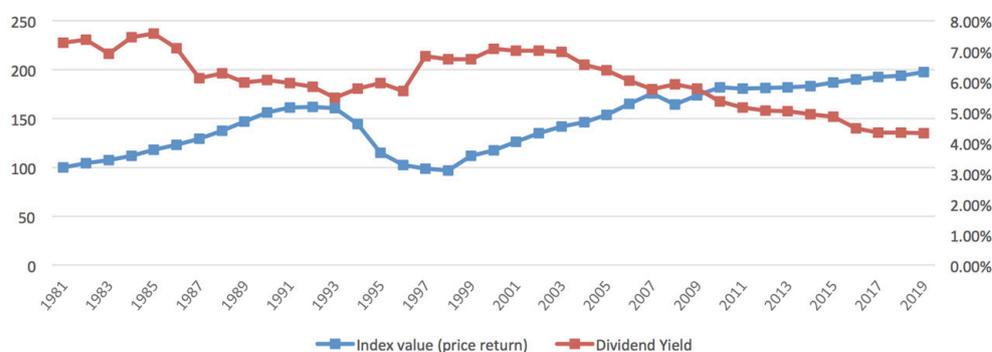
4.1 Performance analysis

Our first step in analysing the performance of an SCPI is to decompose its total return into a price return and a dividend yield component. This is consistent with the fact that SCPIs are seen and marketed as income-generating products. The decomposition will later allow us to enrich the cross-sectional performance analysis and provide insights into the source of outperformance of some SCPIs compared to their peers.

Exhibit 10 applies the suggested decomposition to the EDHEC IEIF Commercial Property (France) Index. Note that throughout this section we use the definitions (d1), (d2) and (d3) presented in Section 3.2 for the calculation of total return, price return and dividend yield.

The general observation is that the price–return index follows a long-term moderate upward trend, matched by a long-term downward trend in dividend yield, interrupted by a large sell-off during the 1990s when the French SCPI market suffered from the combination of a real estate crisis (triggered by a European economic recession in 1992–1993) and a regulation-driven liquidity crisis (see Section 2.4.2). Also, the fluctuations and joint dynamics of the two lines indicate some form of synchronicity, with the dividend yield looking like a simple “inverse of price”. Using definition (d3) in Section 3.2, it is possible to attribute the change in index dividend yield over a period to a combination of a change in index price and a change in index dividend amount. Over the 1981–2019 period presented in Exhibit 10, we calculate that the decrease in annual index dividend yield (from 7.28% to 4.31%) is entirely driven by the change (increase) in index price, with the dividend amount even slightly increasing over the period. However, the same attribution exercise over the 2004–2019 period shows that approximately one quarter (26%) of the decrease in dividend yield (from 6.56% to 4.31%) is driven by a decrease of about -12% in the actual dividend amount, while the

Exhibit 10: Price-return value and dividend yield of the EDHEC IEIF Commercial Property (France) Index from 1981 to 2019



Notes: The solid blue line (lhs axis) represents the price-return index value rebased at 100 in 1981. The solid red line (rhs axis) represents the annual dividend yield of the index.

4. SCPI Risk and Performance Analysis

remaining three-quarters (74%) are explained by an increase in index price. In summary, while the decline in the dividend yield of the index over the past 40 years is primarily due to a long-term increase in real estate prices (hence the "inverse of price" shape observed in Exhibit 10), the past 15 years also witnessed a reduction in absolute rental income that also contributed to the dividend yield compression.

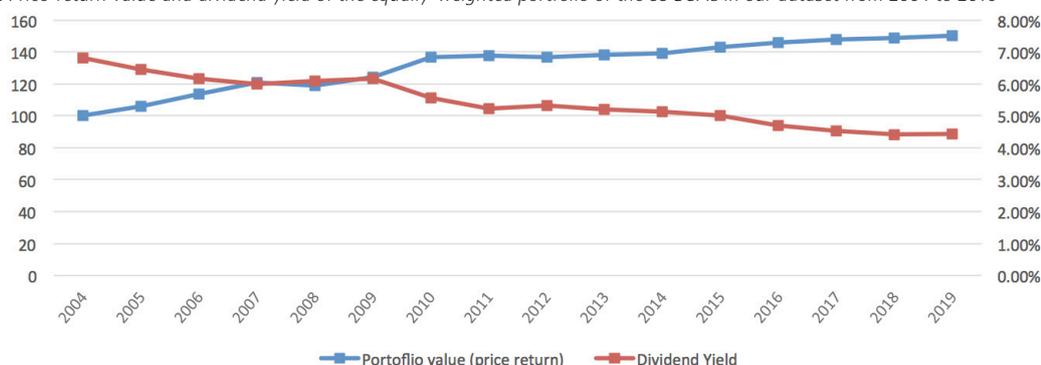
The same decomposition of total return performance (into price return and dividend yield) applied to an equally-weighted (EW) portfolio of the 53 SCPIs in our dataset leads to similar results (albeit for a shorter period, from 2004 to 2019), as seen in Exhibit 11. We observe the same long-term trends in price return portfolio value and dividend yield as well as the same inverse relationship between the portfolio value and its dividend yield.

We nevertheless note a slight difference between the evolution of the index value in Exhibit 10 and that of the EW portfolio value in Exhibit 11. Over the 2004–2019 period, the value of the EW portfolio of 53 SCPIs grew by a factor of 1.50x while the value of the index only grew by a factor

of 1.35x. This translates into annual average (log-) returns of 2.71% and 2.00% respectively and indicates a possible impact of weighting schemes on performance since the index is capitalisation-weighted ("cap-weighted"). The inefficiency and underperformance of cap-weighted indices have been extensively documented in the equity-related academic literature (see for example Grinold (1992) or Amenc et al. (2010)). It is difficult to assess whether Exhibits 10 and 11 provide evidence of a similar effect in SCPI portfolios because our 53 SCPIs are not the exact constituents of the EDHEC IEIF Commercial Property (France) Index. We control for this effect and present some results using our dataset in Section 6.3.

The analysis of aggregate time-series data is interesting to highlight macro-level behaviours, but it does not allow us to distinguish between SCPIs' performance within the universe. We therefore move to a cross-sectional analysis of total returns, price returns and dividend yields, starting with Exhibit 12.

Exhibit 11: Price-return value and dividend yield of the equally-weighted portfolio of the 53 SCPIs in our dataset from 2004 to 2019



Notes: The solid blue line (lhs axis) represents the price-return portfolio value rebased at 100 in 2004. The solid red line (rhs axis) represents the annual dividend yield of the portfolio.

4. SCPI Risk and Performance Analysis

Exhibit 12: Cross-section of total return, price return and dividend yield (2003–2019 averages)



Notes: The solid blue line represents the 2003–2019 average annual total return for each of the 53 SCPIs in our dataset, in ascending order from left to right. The solid orange and grey lines respectively represent the corresponding average annual price return and average annual dividend yield for each SCPI.

Exhibit 12 illustrates the broad range of performances amongst the 53 SCPIs of our dataset. The average annual total returns over the sample period (blue line) vary from 5.2% to 13.4%, a significant discrepancy over a 16-year horizon. In contrast, we note that differences in average dividend yields are relatively small, with yields slightly oscillating around a 5.5% mean level, with lows and highs at 4.4% and 6.6% respectively. The main driver of performance is therefore the average price return, which varies as much as the total return (going from -0.6% to 7.6%) across the universe of SCPIs.

Put another way, despite being the largest contributor to total return (around three-quarters of the total return of the EDHEC IEIF Commercial Property (France) Index), the dividend yield plays little role in differentiating across SCPIs' performances. SCPIs that delivered the strongest total return performance over the period are those whose price return performance was the strongest and, conversely, the lowest total return performances coincide with poor

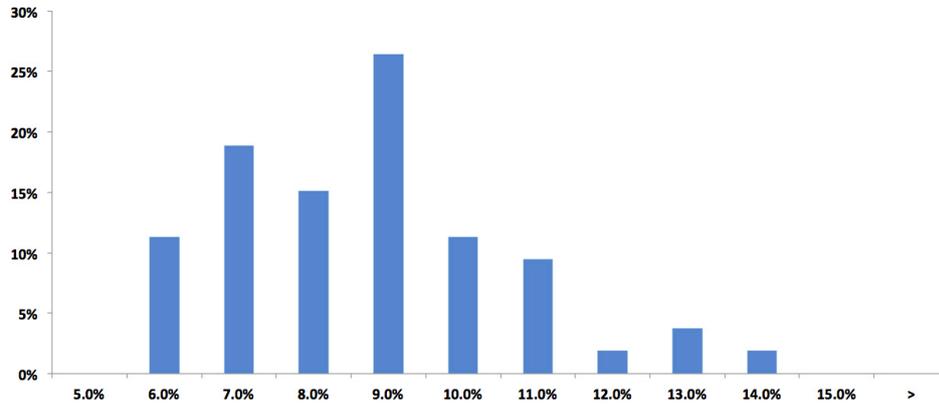
price return performances. The role of price return as a driver of total returns is also confirmed when looking at marginal contributions to the cross-sectional volatility of total returns (see Menchero and Davis (2011) for an introduction to the concept of marginal contribution to risk): the marginal contributions of price return and dividend yield are respectively equal to 89% and 11%. This is an interesting finding considering that SCPI marketing strategy is often based on the attractiveness of the dividend yield offered to new investors.

Exhibits 13, 14 and 15 confirm this cross-sectional analysis of performance by showing the empirical distributions for each of the three drivers of performance (total return, price return and dividend yield).

We see that the distributions of total returns (Exhibit 13) and price returns (Exhibit 14) are very similar in shape, despite having a very different mean level (the difference being effectively the dividend yield). This is further

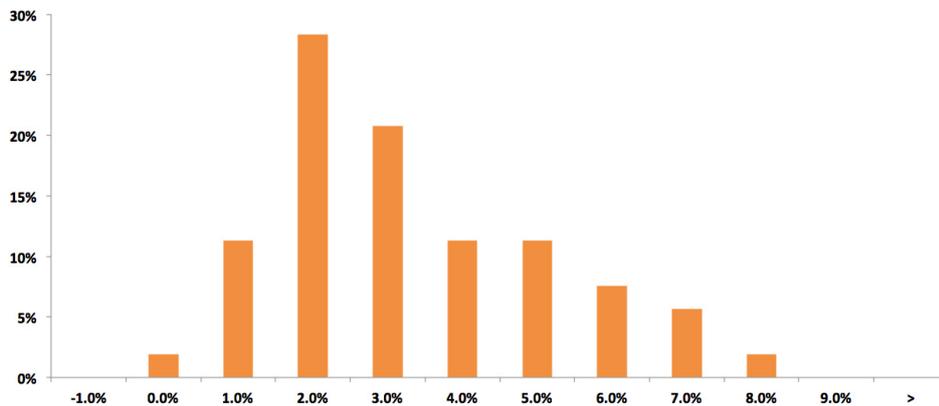
4. SCPI Risk and Performance Analysis

Exhibit 13: Cross-sectional distribution of annual total returns (2003–2019 averages)



Notes: For each of the 53 SCPIs we compute the 2003–2019 average of annual (log-) total returns. The 53 values obtained are summarised in the histogram above.

Exhibit 14: Cross-sectional distribution of annual price returns (2003–2019 averages)



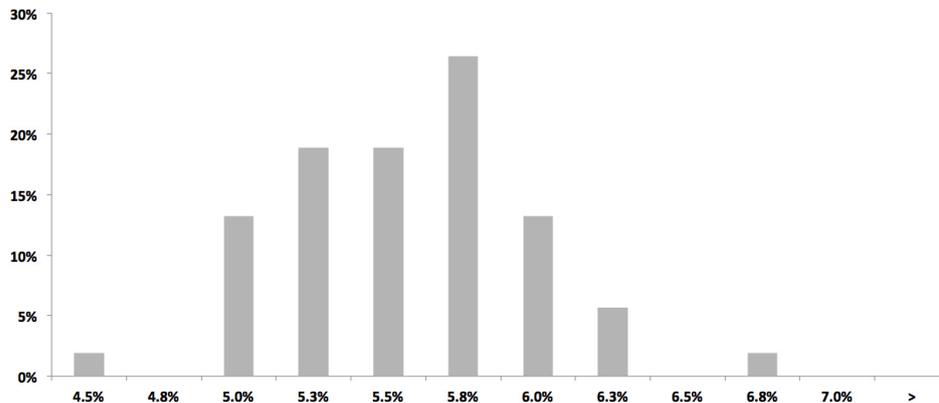
Notes: For each of the 53 SCPIs we compute the 2003–2019 average of annual (log-) price returns. The 53 values obtained are summarised in the histogram above.

confirmed by comparing empirical moments of the distributions. The cross-sectional standard deviation of total returns and price returns are respectively 1.9% and 1.8%, while the cross-sectional skewness of total returns and price returns are respectively 0.76 and 0.70. This contrasts with the distribution of dividend yields (see Exhibit 15), which shows much less dispersion around its mean with a cross-sectional volatility of only 0.4%. The distribution of dividend yields also appears to be a lot more

symmetrical (its cross-sectional skewness is equal to 0.26) than that of price returns. One possible interpretation of the positive skewness in the price returns distribution is that the “skill” of the most talented SCPI managers primarily translates into outsized outperformance in terms of capital appreciation rather than extra income.

4. SCPI Risk and Performance Analysis

Exhibit 15: Cross-sectional distribution of annual dividend yields (2003–2019 averages)



Notes: For each of the 53 SCPIs we compute the 2003–2019 average of annual dividend yields. The 53 values obtained are summarised in the histogram above.

4.2 Risk and Risk-Adjusted Performance Analysis

The analysis carried out in the previous section shows that the SCPI universe offers a significant dispersion in terms of performance. We now continue our cross-sectional exploration by turning to the analysis of risk and risk-adjusted performance. Our goal remains the potential detection of signs of dispersion within the SCPI universe, which would encourage SCPI investors to consider the benefits of selection and allocation decisions.

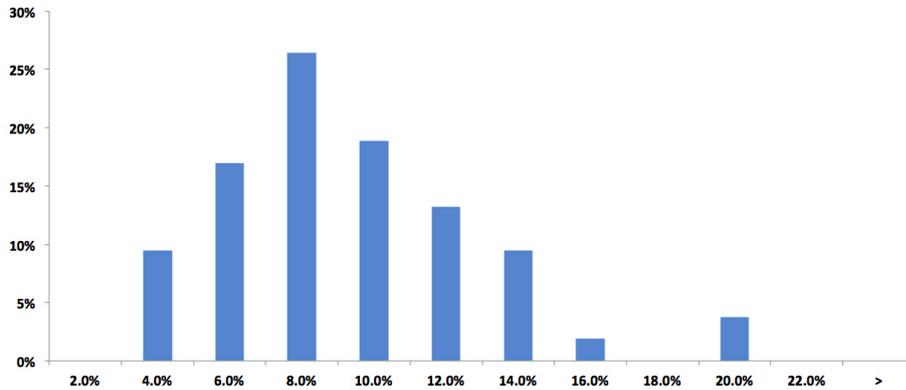
Given the relative scarcity of SCPI data, we use simple metrics for our risk and risk-adjusted performance analyses, namely volatility and the ex-post Sharpe ratio.

As per Exhibit 16, we find that the time-series volatility of total returns, our primary measure of risk, can vary dramatically across the 53 SCPIs of our universe. Indeed, the distribution shows a large level of dispersion around its mean, and the (annual) volatility levels go from 2.8% to

20.0%. This is close to the level of dispersion one would normally observe across asset classes so it is interesting to see it within the SCPI universe. The nature of SCPI data requires caution, however, which explains our attempts to correct for possible biases in Section 3. In particular, the maximum volatility of 20.0% could be seen as an outlier since it corresponds to two SCPIs that converted from closed-end to open-end and experienced a very large (positive) return the year they converted. But it is not unexpected to observe a large jump in price at the time of conversion because any liquidity discount previously reflected in the price (given the market-based valuation of closed-end SCPIs) would vanish once the fund becomes open-end. Aside from these two highlighted data points, the most volatile SCPIs in our universe are closed-end and do not raise any specific concern given their market-based valuation. We therefore view the cross-sectional discrepancy displayed in Exhibit 16 as representative of actual dispersion in risk and as supporting evidence that selection and allocation decisions would add value for SCPI investors.

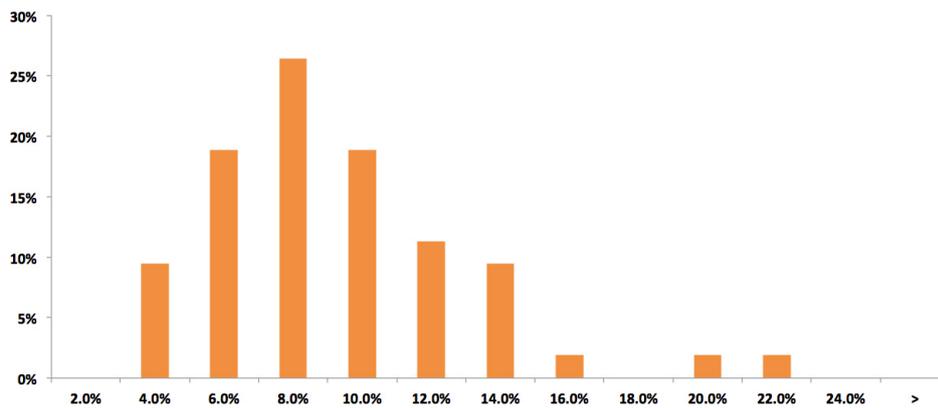
4. SCPI Risk and Performance Analysis

Exhibit 16: Cross-sectional distribution of annual total return volatilities (2003–2019)



Notes: For each of the 53 SCPIs we use the 2003–2019 annual volatility of total returns estimated in Section 3. This estimate incorporates our statistical treatments for smoothing and infrequent data. The 53 values are summarised in the histogram above.

Exhibit 17: Cross-sectional distribution of annual price return volatilities (2003–2019)



Notes: For each of the 53 SCPIs we compute a 2003–2019 annual volatility of price returns, using a sample of adjusted price returns. As explained in Section 3.4.5, the adjustments account for smoothing but do not correct for infrequent data issues. The 53 values are summarised in the histogram above.

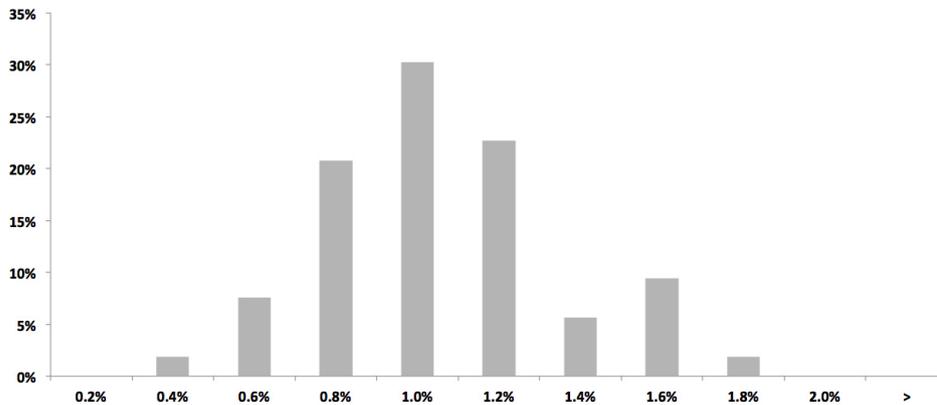
We further analyse the cross-section of the total return volatilities by examining (see Exhibits 17 and 21) two of its underlying components, namely the cross-section of price return volatilities and the cross-section of dividend yield volatilities.

The findings are consistent with those presented in Section 4.1. The main driver of differences between total return historical volatilities are the differences between price return historical

volatilities. Put another way, price returns explain the dispersion in risk across SCPIs (in addition to explaining the dispersion in performance, as seen in Section 4.1). This is evidenced by the striking similarities between Exhibit 16 and Exhibit 17, showing that the cross-sectional distribution of volatilities is roughly the same, whether we look at total returns or price returns. The means of the two distributions are respectively 8.5% and 8.3%, while their standard deviations are almost identical and equal to 3.7%.

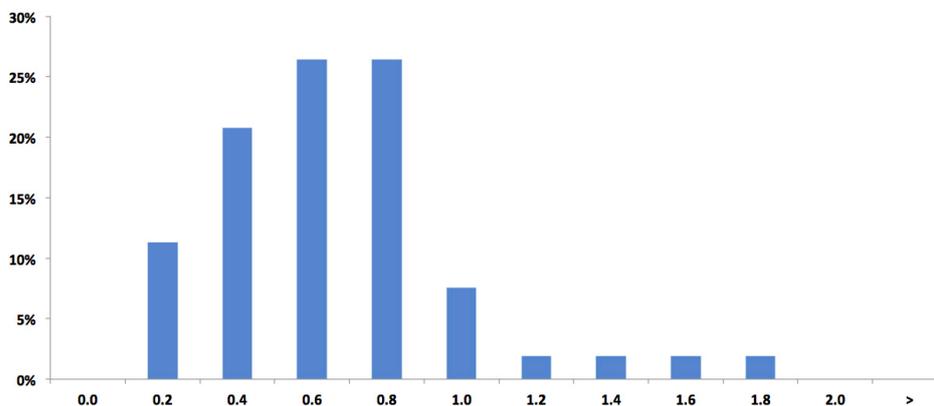
4. SCPI Risk and Performance Analysis

Exhibit 18: Cross-sectional distribution of annual dividend yield volatilities (2003–2019)



Notes: For each of the 53 SCPIs we compute a 2003–2019 annual volatility of dividend yields, using a sample of adjusted dividend yields. As explained in Section 3.4.5, the adjustments account for smoothing but do not correct for infrequent data issues. The 53 values are summarised in the histogram above.

Exhibit 19: Cross-sectional distribution of ex-post Sharpe ratios of total returns (2003–2019)



Notes: For each of the 53 SCPIs we compute the 2003–2019 ex-post Sharpe ratio of total returns, using the 2003–2019 average of annual (log-) total returns as well as the 2003–2019 annual volatility of total returns estimated in Section 3. The volatility estimate incorporates our statistical treatments for smoothing and infrequent data. The 53 values are summarised in the histogram above.

Exhibit 18 is a natural consequence of the above findings as well as the performance analysis carried out in Section 4.1. We first observe that the mean level of dividend yield historical volatility is low and equal to 1.0%. This is consistent with Section 4.1: dividend yields do not vary much in value, certainly less than price returns, and we therefore expect the dividend volatility to be low and certainly lower than the price return volatility. Additionally, since

price return volatilities also explain almost all the dispersion of total return volatilities, there is "not much left" to be explained by dividend yield volatilities, hence the very low level of dispersion in dividend yield risk.

The review of the cross-section of risk-adjusted returns (Exhibit 19) confirms our findings so far. There is a large dispersion in ex-post Sharpe ratios achieved by the 53 SCPIs in our dataset, ranging

4. SCPI Risk and Performance Analysis

from 0.24 to 1.86, with a material right tail which could be regarded as further supporting evidence for the benefits of a selection process, assuming that observable attributes can predict such cross-sectional differences in risk-adjusted performance.

4.3 Dispersion in the SCPI Universe

We conclude Section 4 with a brief (and somewhat anecdotal) review of the SCPI sector's evolution, and how this further supports the case for selection and allocation.

The two previous sections provide statistical evidence of the wide dispersion in performance and risk within the SCPI universe. It is comforting that such dispersion can be qualitatively reconciled with the evolution of the sector and the fact that over time SCPIs have been pursuing a wider range of investment strategies. This strategic diversification clearly enhances the potential benefits of selection and allocation decisions for SCPI investors.

We can list four trends that illustrate the move towards "differentiation" amongst SCPIs.

The first is diversification in other asset categories, namely Retail and Specialised/Alternatives. Retail has indeed traditionally represented large exposure for listed French REITs, but less so for SCPIs that have focused on Offices. Specialised/Alternatives is seen as a promising new source of risk-adjusted performance, although the track record was not deemed long enough to be included in our study.

The second trend is somewhat related to the first, as investments in the Specialised/Alternatives category also lead to innovative income models for SCPIs. For example, it is not uncommon for SCPIs to own furniture and equipment, and generate further income through the provision of services, although the portion of non-rental income is subject to limits to ensure the fundamental purpose of the SCPI remains unchanged.

The third trend is geographic diversification and the larger inclusion of international (i.e. not French) assets in SCPIs' portfolios, especially European real estate. The share of "Europe ex-France" assets in SCPIs' portfolios was 12% in 2018, compared to 2% in 2013. Additionally, approximately 30% of the total investments made by SCPIs in 2018 and 2019 were located in Europe ex-France. One of the drivers of geographic diversification appears to be the high level of capital inflows, which somewhat exceed the natural capacity of the domestic (French) market, pushing IMCs to look for more attractive opportunities abroad.

The fourth trend is the use of leverage. As mentioned in Section 2, SCPIs have been increasing their levels of Loan-To-Value (LTV) for the past 5 years, and this will no doubt create more dispersion in future risk-adjusted performances.

4. SCPI Risk and Performance Analysis

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

In the previous section, we have documented the presence of a relatively high level of dispersion in both performance and risk indicators prevailing within the universe of SCPIs. These results suggest that investor welfare can be enhanced via suitable fund selection decisions.

The purpose of this section is precisely to go one step further and search for observable SCPI attributes that may help explain such cross-sectional dispersion and may in turn be used as the basis for SCPI selection decisions. An exhaustive search of value-adding attributes, including attributes inferred or constructed from SCPIs' financial statements, and the rigorous design of an SCPI selection process are outside the scope of this paper and would at the very least require an in-depth out-of-sample analysis. Our ambition here is simply to provide support for such an initiative by testing a few observable attributes and examining their ability to enhance the in-sample risk-adjusted return profile of an SCPI portfolio. In particular, we conduct in-sample testing on empirical average returns to assess the presence of statistically significant differences in the performance of portfolios constructed in accordance with a given SCPI attribute.

The first part of the section proposes a hypothesis-testing framework to analyse differences in average returns. The second part of the section is an attempt to use our dataset to identify relevant and plausible SCPI attributes, i.e. simple selection criteria that seem to have explanatory power with respect to the risk and return profile of the funds.

5.1 Testing for the Difference in Mean Returns of SCPI Portfolios in the Presence of Smoothing and Infrequent Data

In what follows we present a hypothesis-testing framework to compare the mean returns of two SCPIs; the framework can be easily generalised to two SCPI portfolios.

We assume reported returns of SCPIs are subject to smoothing effects in accordance with equation (1) in Section 3.3 and rewrite equation (1) in a generic form for a given SCPI i :

$$r_{t-1,t}^{i,*} = (1 - \alpha)r_{t-1,t}^i + \alpha r_{t-2,t-1}^{i,*} \quad (1'')$$

We assume (see Geltner (1991, 1993a)) that the true economic return $r_{t-1,t}^i$ is "unpredictable", meaning the $(r_{t-1,t}^i)$ are independent and identically distributed (i.i.d.). We also assume that $r_{0,1}^{i,*} = r_{0,1}^i$.

For each SCPI i the series $(r_{t-1,t}^{i,*})$ is stationary (because $0 < \alpha < 1$) and therefore

$$E(r_{t-1,t}^{i,*}) = E(r_{0,1}^{i,*}) = E(r_{0,1}^i) = \mu_i \text{ for every } t \geq 1.$$

Our goal is to select an estimator of the mean return μ_i for every SCPI, which we call $\hat{\mu}_i$, and determine whether any observed difference between $\hat{\mu}_i$ and $\hat{\mu}_j$ is statistically significant, i.e. test whether the null hypothesis $H_0: \mu_i = \mu_j$ (or $H_0: \mu_i \leq \mu_j$) can be rejected at a suitable confidence level.

In order to simplify and enhance the test procedure we choose the sample mean estimator based on the i.i.d. true returns $(r_{t-1,t}^i)$ rather than on the smoothed reported returns $(r_{t-1,t}^{i,*})$:

$$\hat{\mu}_i = \frac{1}{n} \sum_{t=1}^n r_{t-1,t}^i$$

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

The true economic returns are not directly observable so computing $\hat{\mu}_i$ is not a straightforward exercise. We address this issue in a second step in Section 5.1.2, but first we describe the hypothesis-testing procedure assuming $\hat{\mu}_i$ has been computed already.

5.1.1 Testing Procedure

Without making any assumption on the nature of the univariate distribution of $r_{t-1,t}^i$ other than a finite variance, we note that, given two SCPIs i and j , the variable $(\hat{\mu}_i - \hat{\mu}_j)$ asymptotically follows a univariate normal distribution (with zero mean under H_0) because the "return spreads" $(r_{t-1,t}^i - r_{t-1,t}^j)$ are i.i.d. variables. For the same reason, the variance of $(\hat{\mu}_i - \hat{\mu}_j)$ can be easily computed as:

$$\begin{aligned} \text{Var}(\hat{\mu}_i - \hat{\mu}_j) &= \frac{1}{n} \text{Var}(r_{0,1}^i - r_{0,1}^j) \\ &= \frac{1}{n} [\text{Var}(r_{0,1}^i) - 2\text{Cov}(r_{0,1}^i, r_{0,1}^j) + \text{Var}(r_{0,1}^j)] \end{aligned} \quad (6)$$

We have previously estimated $\text{Var}(r_{0,1}^i)$, $\text{Var}(r_{0,1}^j)$ and $\text{Cov}(r_{0,1}^i, r_{0,1}^j)$ using a combination of desmoothing and trade-to-trade regression techniques (after having empirically estimated α), and so we have all the information required to construct an asymptotic test.

Formally, we follow the *heteroscedasticity and autocorrelation robust* (HAC) kernel estimation procedure described in Ledoit and Wolf (2018), although our working assumptions (i.i.d. returns) and our specific focus on the testing of mean returns significantly simplify the calculations they present in their paper. We also note that the known shortcoming of HAC inference mentioned by Ledoit and Wolf (2018) (see Andrews (1991)),

namely that for small sample sizes a true null hypothesis gets rejected too often compared to the selected nominal significance level, is somewhat mitigated by our use of i.i.d. economic returns $(r_{t-1,t}^i)$ rather than smoothed returns $(r_{t-1,t}^{i*})$. For example, the simulation results presented in Table V in Andrews (1991) report true confidence levels of 92.8% and 91.5% for a 95% nominal confidence interval for two heteroscedastic models with no presence of autocorrelation. When a Lag 1 autocorrelation of 50% is assumed, the true confidence levels respectively drop to 87.4% and 89.5%.

Introducing the notations used in Ledoit and Wolf (2018), we define

$$\begin{aligned} \mathbf{v}^t &= (\mu_i, \mu_j) \text{ and } \hat{\mathbf{v}}^t = (\hat{\mu}_i, \hat{\mu}_j) \\ f(\mathbf{a}, \mathbf{b}) &= \mathbf{a} - \mathbf{b} \\ \Delta = f(\mathbf{v}) &= \mu_i - \mu_j \text{ and } \hat{\Delta} = f(\hat{\mathbf{v}}) = \hat{\mu}_i - \hat{\mu}_j \end{aligned}$$

$\text{Var}(r_{t-1,t}^i)$ is assumed finite, which implies the following convergence in distribution as $n \rightarrow +\infty$ $\sqrt{n}(\hat{\Delta} - \Delta) \xrightarrow{d} N[0, \nabla f(\mathbf{v})^t \Psi \nabla f(\mathbf{v})]$ where Ψ is the asymptotic (2x2) covariance matrix of $\sqrt{n}\hat{\mathbf{v}}$.

$$\Psi = \begin{pmatrix} \text{Var}(r_{0,1}^i) & \text{Cov}(r_{0,1}^i, r_{0,1}^j) \\ \text{Cov}(r_{0,1}^i, r_{0,1}^j) & \text{Var}(r_{0,1}^j) \end{pmatrix}$$

Assuming a consistent estimator $\hat{\Psi}$ of Ψ is available, and noting that $\nabla f(\mathbf{a}, \mathbf{b})^t = (1, -1)$, the authors then compute $s^2(\hat{\Delta})$, a consistent estimator of the asymptotic variance of $\hat{\Delta}$:

$$s^2(\hat{\Delta}) = \frac{\nabla f(\hat{\mathbf{v}})^t \hat{\Psi} \nabla f(\hat{\mathbf{v}})}{n} = \frac{1}{n} (\hat{\Psi}_{11} - 2\hat{\Psi}_{12} + \hat{\Psi}_{22}) \quad (7)$$

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

Again the i.i.d. argument allows us to simplify the expression of the HAC estimator $\hat{\Psi}$ suggested by Ledoit and Wolf (2018) as follows:

$$\hat{\Psi} = \hat{\Psi}_n = \frac{1}{n-2} \sum_{t=1}^n \begin{pmatrix} r_{t-1,t}^i - \hat{\mu}_i \\ r_{t-1,t}^j - \hat{\mu}_j \end{pmatrix} \begin{pmatrix} r_{t-1,t}^i - \hat{\mu}_i \\ r_{t-1,t}^j - \hat{\mu}_j \end{pmatrix}^t$$

This leads to the following matrix form:

$$\hat{\Psi} = \begin{pmatrix} \frac{1}{n-2} \sum_{t=1}^n (r_{t-1,t}^i - \hat{\mu}_i)^2 & \frac{1}{n-2} \sum_{t=1}^n (r_{t-1,t}^i - \hat{\mu}_i)(r_{t-1,t}^j - \hat{\mu}_j) \\ \frac{1}{n-2} \sum_{t=1}^n (r_{t-1,t}^i - \hat{\mu}_i)(r_{t-1,t}^j - \hat{\mu}_j) & \frac{1}{n-2} \sum_{t=1}^n (r_{t-1,t}^j - \hat{\mu}_j)^2 \end{pmatrix} \quad (8)$$

We note that $\hat{\Psi}$ is the usual sample covariance matrix multiplied by $\frac{n-1}{n-2}$. We substitute equation (8) into equation (7) to specify the asymptotic variance of $\hat{\Delta} = \hat{\mu}_i - \hat{\mu}_j$ explicitly:

$$s^2(\hat{\Delta}) = \frac{1}{n} \frac{n-1}{n-2} (\hat{\sigma}_i^2 - 2\hat{\sigma}_{ij} + \hat{\sigma}_j^2) \quad (7')$$

where $\hat{\sigma}_i^2$, $\hat{\sigma}_{ij}$ and $\hat{\sigma}_j^2$ are respectively the sample variance estimator of $(r_{t-1,t}^i)$, the sample covariance estimator of $(r_{t-1,t}^i, r_{t-1,t}^j)$ and the sample variance estimator of $(r_{t-1,t}^j)$. We note that equation (7') is very consistent with the somewhat more theoretical equation (6) presented earlier.

As highlighted in Section 3.4, the sample covariance matrix of SCPI returns is subject to estimation biases due to smoothing and infrequent trading as well as high estimation errors in non-diagonal terms because of the general scarcity of SCPI data (which is further compounded by infrequent trading) relative to the dimension of the matrix. Therefore, we choose to compute $s^2(\hat{\Delta})$ by replacing $\hat{\sigma}_i^2$, $\hat{\sigma}_{ij}$ and $\hat{\sigma}_j^2$ in equation (7') with the variance and covariance estimates computed in section 3.4.5 using desmoothing and trade-to-trade regression techniques.

As mentioned earlier, the potential disadvantage of our estimation method is a risk of misspecification (i.e. a modelling risk) that could cause a significant bias. We note that our variance estimator is actually immune to misspecification since our market model does not affect the total variance of returns, but only the breakdown between systematic and idiosyncratic risks. Our proposed variance estimate is therefore equivalent to an unbiased and consistent sample variance estimator that would account for smoothing and infrequent data effects. On the other hand, our correlation estimates (or non-diagonal covariance estimates) are highly specified and could include a large bias in cases where our market model fails to explain the data. As mentioned in Sections 3.4.3 and 3.4.5, we have attempted to mitigate this risk by adjusting those correlation estimates implied by regressions where the market model is not statistically significant. We are aware that our correction, namely imposing a non-zero average correlation to pairs for which the simple market model predicts zero correlation, introduces another form of misspecification risk, but we consider it to be lower than that created by the market model itself.

Ledoit and Wolf (2018) conclude the HAC testing procedure with a p-value expression for the null hypothesis $H_0: \Delta = 0$ once the asymptotic variance $s^2(\hat{\Delta})$ has been estimated:

$$\hat{p} = 2\Phi\left(-\frac{|\hat{\Delta}|}{s(\hat{\Delta})}\right)$$

where Φ is the cumulative distribution function of the standard normal distribution.

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

5.1.2 Computing the Sample Mean Estimator of True Economic Returns

Infrequent data issues (staleness) prevent us from computing $\hat{\mu}_i$ by simply inverting equation (1") and implying the full series ($r_{t-1,t}^i$). However, we do not need to infer every single return $r_{t-1,t}^i$ to calculate $\hat{\mu}_i$. We can apply a summation to equation (1") and use the fact that $r_{0,1}^{i,*} = r_{0,1}^i$ to obtain:

$$r_{0,1}^{i,*} + \sum_{t=2}^n r_{t-1,t}^{i,*} = r_{0,1}^i + (1 - \alpha) \sum_{t=2}^n r_{t-1,t}^i + \alpha \sum_{t=2}^n r_{t-2,t-1}^{i,*}$$

Some simple algebra then leads us to:

$$\hat{\mu}_i = \frac{1}{n} \sum_{t=1}^n r_{t-1,t}^{i,*} - \frac{\alpha}{n(1 - \alpha)} (r_{0,1}^{i,*} - r_{n-1,n}^{i,*}) \quad (9)$$

We can therefore determine $\hat{\mu}_i$ provided we can compute the smoothed total return over the full period (2003–2019) of our analysis, and provided we have access to the first and last smoothed returns in the period. This is far less demanding from a data standpoint than accessing every single return $r_{t-1,t}^{i,*}$, and consequently eliminates a very large chunk of our infrequent trading issues.

We still have 5 SCPIs (out of 53) whose infrequent data problems directly affect the formula proposed in equation (9), although we have determined that the impact on the estimation of $\hat{\mu}_i$ is not material. Indeed, we quantify such impact by first partially differentiating equation (9) with respect to each individual return $r_{t-1,t}^{i,*}$ and then by computing the impact of a one standard deviation move for each of the missing (stale) $r_{t-1,t}^{i,*}$. Our impact analysis shows that a one standard deviation move of stale returns (to be conservative, we consider the sum of absolute sensitivities when more than one relevant return data point is stale) leads to

differences in $\hat{\mu}_i$ ranging from 0.05% to 0.46% (expressed in annual log-return). Considering that we intend to perform hypothesis testing in the context of diversified portfolios with at least 13 SCPI constituents (see Sections 5.2 and 6.3), the end impact on the estimated average annual (log-) return of a portfolio is only 0.08%. Note this is a somewhat conservative estimate that assumes all 5 SCPIs affected by staleness happen to be in the portfolio we wish to test. We therefore consider the estimation biases introduced by infrequent data to be non-material in the context of the hypothesis testing of mean portfolio returns and choose to compute $\hat{\mu}_i$ using stale datapoints.

5.2 Identification of Relevant Cross-Sectional Attributes

In what follows, we segment our universe of 53 SCPIs into several groups in accordance with 8 chosen observable attributes, and in the corresponding Sections 5.2.1 to 5.2.8 we compare the risk and/or return profiles of the groups to determine whether the segmentation rule can help explain differences in risk and/or returns across the database. Groups relating to the *same* attribute are mutually exclusive and collectively exhaustive by design: there is no SCPI overlap between them and the union of their constituents is exactly equal to our dataset of 53 SCPIs.

We take a systematic approach (with the exception of Section 5.2.8) and produce the same 3 metrics for each group: the cross-sectional average of the time-series average annual total returns of the group constituents over the 2003–2019 period (a *return* metric), the cross-sectional average of the time-series volatilities of total return of

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

the group constituents over the period (a *risk* metric), and the cross-sectional average of the (time-series) ex-post Sharpe ratios achieved by the group constituents over the period (a *risk-adjusted return* metric). When referring to (total) return, risk or risk-adjusted return in Sections 5.2.1 to 5.2.7, we implicitly refer to these 3 metrics. For illustration purposes, we also show the graph of the total return performance time-series of the equally-weighted *portfolio* of group constituents (which we call a "group portfolio") since it is an intuitive way to visualise the full time-series of the cross-sectional averages of annual total return performance and it may possibly help uncover specific "regimes" of performance. We then qualitatively comment on the results and "select" a group if (1) we find our attribute to be discriminating enough with one portfolio emerging with materially more attractive metrics over the period, and (2) if we can identify an economically plausible explanation for the differences in performance or risk. When reporting p-values in Sections 5.2.1 to 5.2.7, we implicitly refer to p-values calculated based on the hypothesis-testing framework described in Section

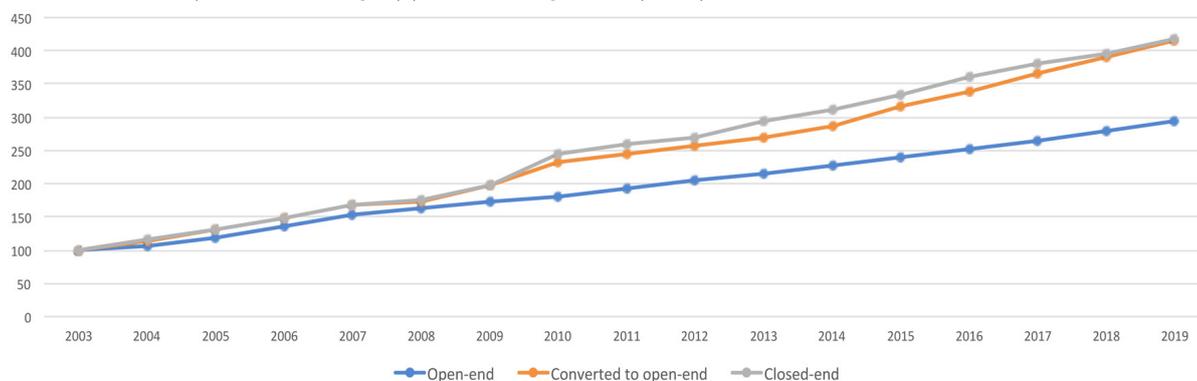
5.1. The final sub-section (5.2.8) is constructed differently due to the nature of the observable attribute we intend to analyse.

5.2.1 Capital Type Attribute

The Capital Type attribute is defined in the most natural way, which is to segment the universe into 3 groups: open-end SCPIs (the 'Open-end' group), closed-end SCPIs (the 'Closed-end' group) and SCPIs that are currently open-end but converted from closed-end during the 2003–2019 period (the 'Converted to open-end' group).

The results are presented in Exhibits 20 and 21. We find very little difference in terms of return, risk or Sharpe ratio between the 'Converted to open-end' and 'Closed-end' groups, but the 'Closed-end' and 'Converted to open-end' groups materially outperformed 'Open-end' both in terms of total return (p-values of 11% and 7% for differences in mean returns between the respective pairs of group portfolios) and in terms of risk-adjusted total return.²⁸ There is however no formal economic link between an SCPI's capital type and the strategy it pursues or the performance

Exhibit 20: Total return performance of the group portfolios relating to the Capital Type attribute from 2003 to 2019

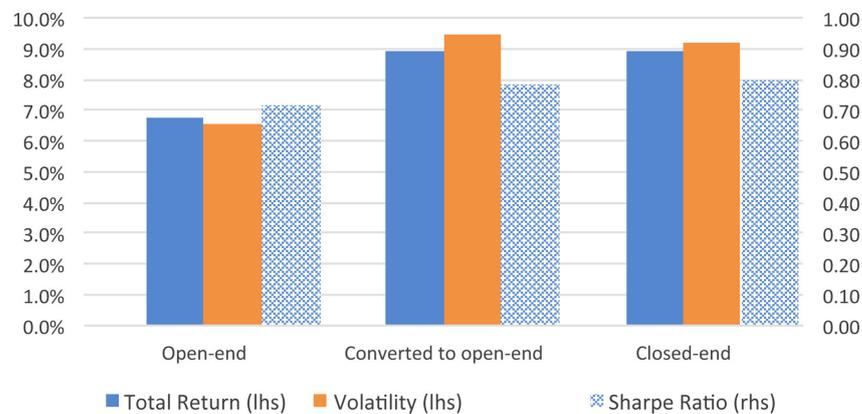


Notes: Each portfolio is rebased at 100 as of 31 December 2003 and grows at the total return rate. The solid blue (respectively orange, and grey) line represents the evolution of the value of the 'Open-end' (respectively 'Converted to open-end' and 'Closed-end') portfolio.

28 - Note that the 'Open-end' average risk-adjusted return would have been very different (and quite likely greater than that of 'Closed-end' and 'Converted to open-end') had we not applied the statistical techniques described in Section 3.4 to account for the presence of smoothing and infrequent data.

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

Exhibit 21: Cross sectional averages of total return, volatility and Sharpe ratio for the groups relating to the Capital Type attribute (2003–2019)



Notes: For each group we compute, for the 2003–2019 period, the cross-sectional average of the time-series average annual (log-) total returns, the cross-sectional average of the annual volatility estimate of total returns (incorporating statistical treatments for smoothing and infrequent data), and the cross-sectional average of ex-post Sharpe ratio of total returns. The blue and orange bars (lhs y-axis) respectively represent the average total return and the average volatility, while the pattern-filled bars (rhs y-axis) represent the average Sharpe ratios.

it targets for investors, so the outperformance could be the result of an unknown factor that just happens to be stronger amongst closed-end SCPIs (in Section 5.2.3 we report a strong overlap between closed-end SCPIs and those SCPIs with the smallest AUM), or because the full transfer of liquidity risk to investors allows closed-end SCPIs to invest in less liquid assets than their open-end peers and possibly collect an extra risk premium as a result. It is known that closed-end SCPIs have more flexibility in timing their investments because, unlike open-end SCPIs, they are not forced to invest in times of large capital inflows (with the risk of buying "at the peak"). However, we did not observe any post-conversion underperformance amongst the 'Converted to open-end' group, so the timing argument cannot fully explain the results in Exhibits 20 and 21. In the absence of a natural economic link between fund capital type and risk-adjusted performance, we do not propose to use this attribute in the selection process.

5.2.2 Asset Category Attribute

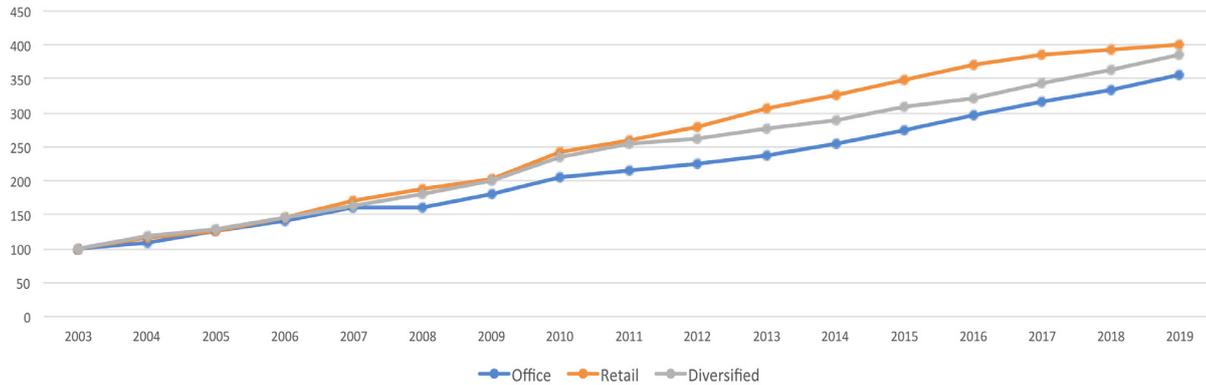
The Asset Category attribute relies on the segmentation already implemented in the IEIF database (see the definition in Section 2.3), leading to 4 groups mirroring key areas of real estate investments and expertise: 'Office', 'Retail', 'Specialised' and 'Diversified'.

We exclude the 'Diversified' group from our analysis though because our dataset only has one single Specialised SCPI (see Section 3.1 for the reasons of the relative under-representation of Specialised SCPIs in our dataset), whose average historical total return cannot be considered as a reasonable estimate of the expected return of a 'Specialised' group.

The time-series results presented in Exhibit 22 show that the 'Retail' group portfolio slightly outperformed the two others over the 2003–2019 period, although the spread in total return is largely due to early outperformance (especially

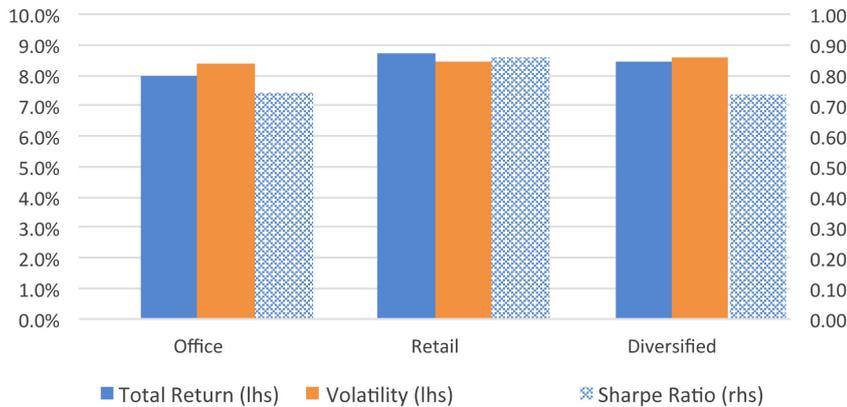
5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

Exhibit 22: Total return performance of the group portfolios relating to the Asset Category attribute from 2003 to 2019, with the Specialised group removed



Notes: Each portfolio is rebased at 100 as of 31 December 2003 and grows at the total return rate. The solid blue (respectively orange, grey) line represents the evolution of the value of the 'Office' (respectively 'Retail' and 'Diversified') portfolio.

Exhibit 23: Cross-sectional averages of total return, volatility and Sharpe ratio for the groups relating to the Asset Category attribute from 2003 to 2019, with the 'Specialised' group removed



Notes: For each group we compute, for the 2003–2019 period, the cross-sectional average of the time-series average (log-) total returns, the cross-sectional average of the annual volatility estimate of total returns (incorporating statistical treatments for smoothing and infrequent data), and the cross-sectional average of ex-post Sharpe ratio of total returns. The blue and orange bars (lhs y-axis) respectively represent the average total return and the average volatility, while the pattern-filled bars (rhs y-axis) represent the average Sharpe ratios.

during the 2008 financial crisis) and reduced in recent years. In fact, 'Retail' underperformed the two other portfolios over the last 5 years in the period (2014–2019), possibly because of a wide structural effect whereby the income of middle-class and modest households in developed economies had been under pressure since 2008. According to the McKinsey Global Institute²⁹, between 60 and 70% of households in 25

advanced economies (63% in France) experienced flat or falling income between 2005 and 2014. This compared with less than 2% between 1993 and 2005. The resulting income effect led to reduced discretionary spending which primarily impacted retail shops. And the recent growth of e-commerce further accelerated the underperformance of traditional "brick-and-mortar" retail shops.

29 - McKinsey Global Institute report, 2016, Poorer than their parents? Flat or falling incomes in advanced economies: <https://www.mckinsey.com/featured-insights/employment-and-growth/poorer-than-their-parents-a-new-perspective-on-income-inequality>

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

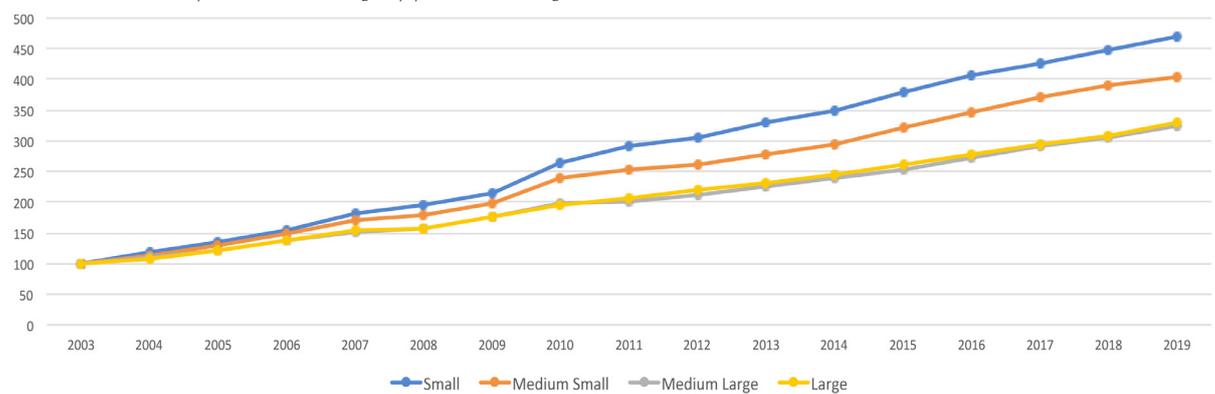
Exhibit 23 does not show any material difference between 'Retail' and 'Office' in terms of return (p-value = 37%), risk or risk-adjusted return over the full 2003–2019 period. Perhaps more surprisingly, the 'Diversified' group does not outperform the other two in terms of Sharpe ratio, something one would have naturally expected from a set of SCPIs that are by design diversifying their asset category exposure (note that the slight outperformance in average Sharpe

ratio reported for the 'Retail' group is entirely driven by one SCPI in the group so it cannot be considered significant). We therefore do not find the Asset Category attribute to be discriminating enough and do not propose to use it in the selection process.

5.2.3 Fund Size Attribute

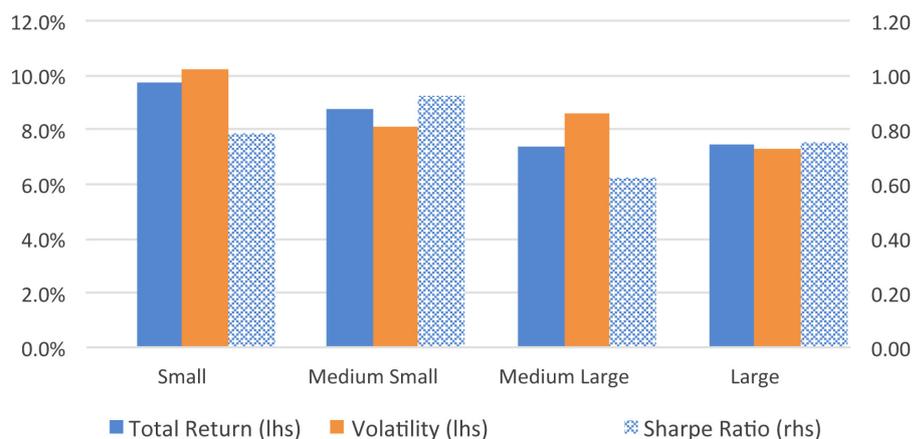
We define the "size" of an SCPI as its annual average AUM during the 2003–2019 period (using

Exhibit 24: Total return performance of the group portfolios relating to the Fund Size attribute from 2003 to 2019



Notes: Each portfolio is rebased at 100 as of 31 December 2003 and grows at the total return rate. The solid blue (respectively orange, grey, and yellow) line represents the evolution of the value of the 'Small' (respectively 'Medium' and 'Large') portfolio

Exhibit 25: Cross-sectional averages of total return, volatility and Sharpe ratio for the groups relating to the Fund Size attribute (2003–2019)



Notes: For each group we compute, for the 2003–2019 period, the cross-sectional average of the time-series average annual (log-) total returns, the cross-sectional average of the annual volatility estimate of total returns (incorporating statistical treatments for smoothing and infrequent data), and the cross-sectional average of ex-post Sharpe ratio of total returns. The blue and orange bars (lhs y-axis) respectively represent the average total return and the average volatility, while the pattern-filled bars (rhs y-axis) represent the average Sharpe ratios.

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

year-end AUMs). We then rank SCPIs by size and define a Fund Size attribute by evenly splitting the population into 3 groups: 'Small', 'Medium' and 'Large'.

The results in Exhibits 24 and 25 show that total return and volatility both tend to decrease with Fund Size, indicating that smaller SCPIs tend to follow "high return/high risk" strategies while larger SCPIs may implement "low return/low risk" strategies. The p-value for the difference in mean returns between 'Small' and 'Large' (respectively 'Small' and 'Medium Large') is 6% (respectively 3%) and indicates there may be a "size effect" at play in the SCPI market. The debate on the existence of a size factor in equities has been ongoing for nearly three decades (see Fama and French (1993), and Alquist et al. (2018)) and has not shown any recent sign of abating (see Asness (2020), and Goltz and Luyten (2020)) despite an abundance of data. The impact and relevance of the Fund Size attribute has also been documented in the real estate academic literature although the sign of the impact varies (see Fuerst and Matysiak (2013) for an outperformance of larger funds, Guidolin and Pedio (2019) for an outperformance of smaller funds, and Delfim and Hoesli (2016) for a non-monotonic relationship). An attempt to settle the matter for the SCPI market would at least require a more in-depth analysis of small-sized SCPIs to determine whether the differentiating factor is solely the AUM of the fund or whether the latter is a proxy for the size of real estate assets held. For example, we note that 57% of the members of the 'Small' group are members of the 'Low Asset Size' group (see Section 5.2.6) and another 21% (so close to 80% overall) are members of the 'Medium Low Asset

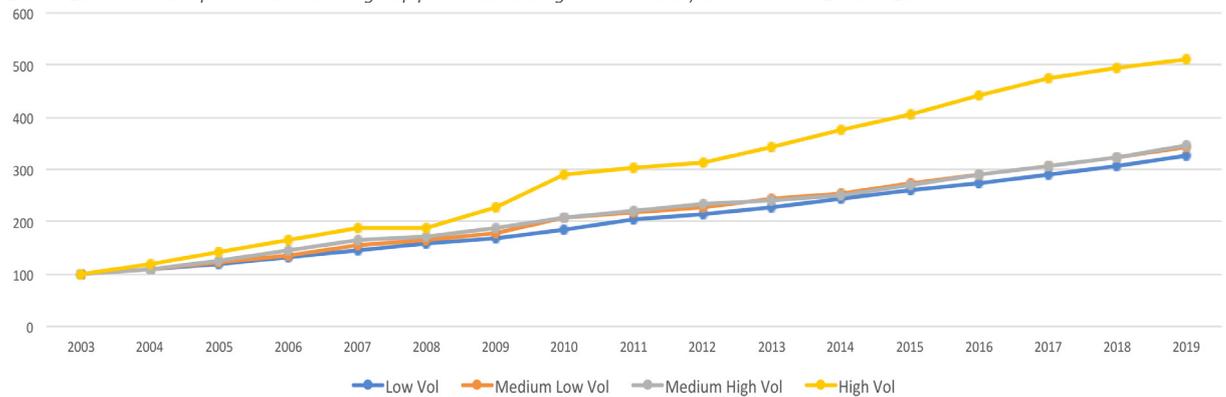
Size' group. This strong overlap translates into a 96% correlation between the group portfolios pertaining to 'Small' and 'Low Asset Size'. It is also worth highlighting that our segmentation is static, meaning members of our 'Small', 'Medium' and 'Large' groups do not vary over time. A worthy refinement of the analysis would consist in constructing dynamic portfolios that account for relative changes in fund size, for example a 'Small' SCPI growing relative to its peers and becoming comparable to 'Medium' or even 'Large' SCPIs throughout the considered investment period. Dynamic portfolios would likely help identify a true "size factor", should such a factor exist for SCPIs. They would also enable a broadening of the analysed set of SCPIs, allowing for the introduction of recently launched funds and for the testing of possible "vintage" effects in the SCPI universe. A dynamic framework would also facilitate the analysis of other naturally fluctuating attributes such as the current dividend yield (a metric closely monitored by industry practitioners; see for instance Reid (2017a)). However, the statistical treatments for smoothing and infrequent data performed in Section 3.4 currently allow for a static framework only, so analysing and comparing the performance and risk of dynamic portfolios will require further research into the accurate measurement of variances and covariances of SCPI portfolios. Such research will also need to consider the practical implementation of dynamic portfolios given the low liquidity and the transaction costs associated with SCPIs. An analysis of financial statements may also show that Size is a placeholder for another risk attribute. For example, Schoeffler (2020) points out that smaller SCPIs tend to use higher levels of financial leverage, which could

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

help explain our results and would add value to a more advanced selection process. Higher levels of leverage may also indirectly inform investors about the managers' own expectations of future asset performance, further enriching the selection process. It is also interesting to note that 85% of the 'Small' group – 11 constituents out of 13 – is made up of closed-end SCPIs (the percentage arguably increases to 92% since one of the 2 remaining SCPIs only converted from closed-end

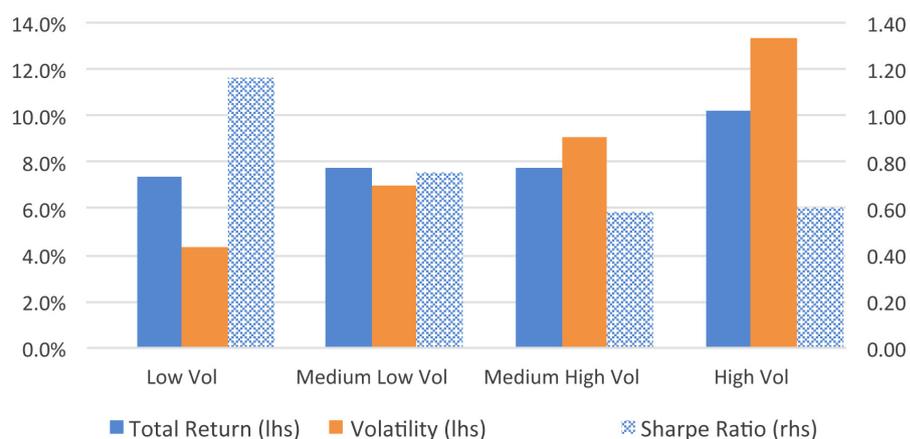
to open-end very recently, in 2017). This overlap translates into a 95% correlation between the group portfolios pertaining to 'Small' and 'Closed-end', which could well "explain" the significant outperformance we reported in Section 5.2.1. These additional characteristics of the 'Small' group provide some support for a plausible explanation of the observed outperformance, such as the ability for a small-sized closed-end fund to invest in assets that i) are small enough

Exhibit 26: Total return performance of the group portfolios relating to the Volatility attribute from 2003 to 2019



Notes: Each portfolio is rebased at 100 as of 31 December 2003 and grows at the total return rate. The solid blue (respectively orange, grey and yellow) line represents the evolution of the value of the 'Low Vol' (respectively 'Medium Low Vol', 'Medium High Vol' and 'High Vol') portfolio.

Exhibit 27: Cross-sectional averages of total return, volatility and Sharpe ratio for the groups relating to the Volatility attribute (2003–2019)



Notes: For each group we compute, for the 2003–2019 period, the cross-sectional average of the time-series average annual (log-) total returns, the cross-sectional average of the annual volatility estimate of total returns (incorporating statistical treatments for smoothing and infrequent data), and the cross-sectional average of ex-post Sharpe ratio of total returns. The blue and orange bars (lhs y-axis) respectively represent the average total return and the average volatility, while the pattern-filled bars (rhs y-axis) represent the average Sharpe ratios.

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

to be overlooked by larger managers, ii) are illiquid enough to be avoided by small open-end funds, iii) can be acquired with financial leverage since the fund is not exposed to the risk of investors redeeming. We therefore propose to use the Fund Size attribute in the selection process.

5.2.4 Volatility Attribute

We define the Volatility attribute by assigning SCPIs to 4 equally-sized groups corresponding to the 4 quartiles of the distribution of total return volatilities estimated in Section 3. We name the groups: 'Low Vol', 'Medium Low Vol', 'Medium High Vol' and 'High Vol'.

The results presented in Exhibits 26 and 27 show a strong outperformance of the 'High Vol' portfolio in terms of total return with p-values of less than 10% for all three pairs of group portfolios. We argue such outperformance is largely explained by an overlap of constituents between the 'High Vol' group and the 'Small' group analysed in the previous section (5.2.3). Indeed, 50% of the 'High Vol' group belongs to the 'Small' group and another 29% (so 79% in total) belongs to the 'Medium Small' group. In line with our proposed explanation (see properties of the 'Small' group in Section 5.2.3), the 'High Vol' group also largely comprises closed-end SCPIs or recently converted SCPIs (respectively 64% and 14% of the group). Moreover, the correlation between the 'Small' and 'High Vol' group portfolios is estimated at 94%, and we find no significant difference in total return between the two group portfolios (p-value = 49%). Turning to the three other groups related to the Volatility attribute, Exhibit 27 shows no significant differences in terms of total return (p-values greater than 50%).

The results in terms of risk metric are hardly surprising. As expected, and by design, the 4 portfolios show material differences in terms of volatility (see Exhibit 27): the average volatility of the 'Medium High Vol' and 'High Vol' groups is 2 to 3 times greater than that of the 'Low Vol' group. Combining this observation with the small differences in terms of total return (excluding the 'High Vol' group) leads to a real estate equivalent of the "low volatility anomaly" that is well known in the equity space, and thus makes the 'Low Vol' group much more attractive than the 'Medium Low Vol' and 'Medium High Vol' groups from a risk-adjusted returns standpoint, although we are conscious of the potential in-sample issues attached to the design of the Volatility groups.

In conclusion, the discriminating power of the Volatility attribute with regards to performance is largely a repeat of the Fund Size attribute. This seems consistent with the explanation we provided for the outperformance of the 'Small' SCPIs, namely that they could structurally afford taking more risk (higher volatility of returns) and get compensated for it. It also means that the Volatility attribute is somewhat redundant in explaining differences in performance. However, based on the findings related to the 'Low Vol' group, we recommend out-of-sample testing (which we leave for further research) of the attribute's discriminating power in terms of risk-adjusted return. If testing proves conclusive, it would support the inclusion of the Volatility attribute in the selection process to inform investors' decisions.

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

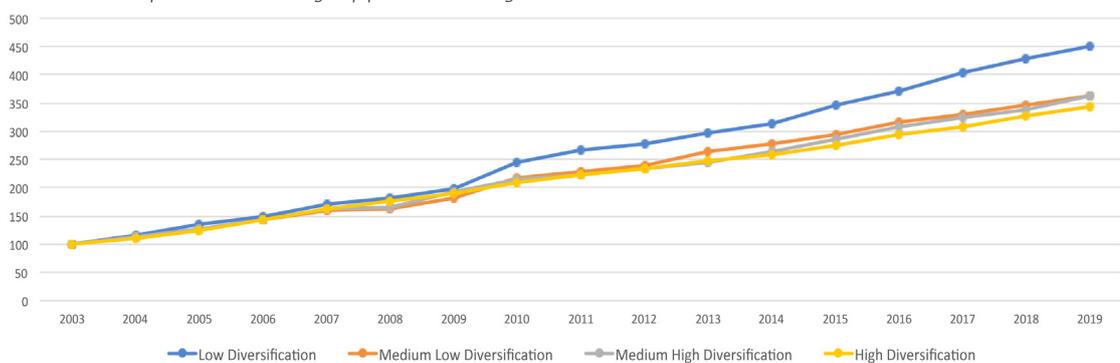
5.2.5 Asset Diversification Attribute

We define the Asset Diversification attribute by looking at the number of assets held by each SCPI, and assigning the population to 4 equally-sized groups corresponding to the 4 quartiles of the distribution of the number of assets. We name the groups: 'Low Diversification', 'Medium Low Diversification', 'Medium High Diversification' and 'High Diversification'.

The results are presented in Exhibits 28 and 29.

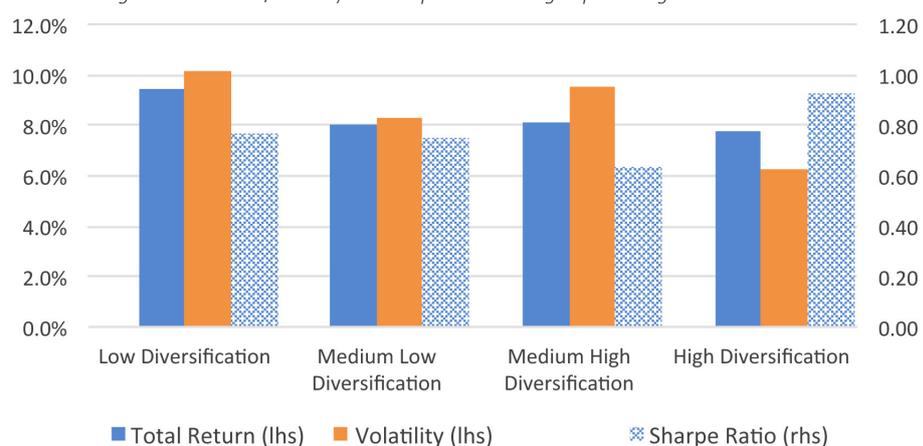
Our data is from 2019 so it would not capture possibly large changes in the ranking (by number of assets) of a given SCPI throughout the 2003–2019 period, but the inherently stable nature of an SCPI portfolio (due to its raison d'être of rental income generation) should, in our view, mitigate this effect.

Exhibit 28: Total return performance of the group portfolios relating to the Asset Diversification attribute from 2003 to 2019



Notes: Each portfolio is rebased at 100 as of 31 December 2003 and grows at the total return rate. The solid blue (respectively orange, grey, and yellow) line represents the evolution of the value of the 'Low Diversification' (respectively 'Medium Low Diversification', 'Medium High Diversification' and 'High Diversification') portfolio.

Exhibit 29: Cross-sectional averages of total return, volatility and Sharpe ratio for the groups relating to the Asset Diversification attribute (2003–2019)



Notes: For each group we compute, for the 2003–2019 period, the cross-sectional average of the time-series average annual (log-) total returns, the cross-sectional average of the annual volatility estimate of total returns (incorporating statistical treatments for smoothing and infrequent data), and the cross-sectional average of ex-post Sharpe ratio of total returns. The blue and orange bars (lhs y-axis) respectively represent the average total return and the average volatility, while the pattern-filled bars (rhs y-axis) represent the average Sharpe ratios.

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

The results in Exhibits 28 show a strong outperformance of the 'Low Diversification' portfolio in terms of total return. A similar analysis to the one conducted in Section 5.2.4 leads us to believe that 'Low Diversification' is another proxy for the 'Small' group and therefore would not add much value in a selection process. Our view is based on a large overlap of constituents (about 70%), a strong correlation between the associated group portfolios (93%), and no significant difference in total return (p-value = 63%). It is also economically plausible that small SCPIs will have fewer opportunities for diversification given the indivisible nature of real estate assets. To a lesser extent, we view the 'High Diversification' group as a proxy for the 'Low Vol' group, with an overlap of 57% (increasing to 71% when considering the 'Medium Low Vol' constituents), a correlation of 90% between corresponding group portfolios, and a statistically non-significant difference in average total return (p-value = 51%). Indeed, Exhibit 29 shows a materially lower level of volatility for the 'High Diversification' group compared to its peers. Also, all else being equal, one would intuitively expect highly diversified SCPIs to belong to the 'Low Vol' group (and present more attractive Sharpe ratios as per Exhibit 29) given the risk-reducing properties of diversification. However, the possible redundancy of the 'High Diversification' group is not necessarily a reason to exclude the Asset Diversification attribute from the selection process because asset diversification is observable ex-ante (unlike low volatility) and is therefore expected to be robust when tested out-of-sample. We therefore propose to retain the Asset Diversification attribute in the selection process as a way of mitigating the risk of in-sample bias that 'Low Vol' may carry (see

our conclusion in Section 5.2.4). We also suggest that future research could usefully analyse SCPIs' financial statements to shed light on the type of diversification implemented by SCPIs to further refine the Asset Diversification attribute. Indeed, the academic literature (see the introduction to Section 6) argues that diversification in commercial real estate is mainly achieved through a diversification of risk factors, including geographic location: an SCPI with fewer assets but located in very different economic regions may achieve more diversification than one with a large number of assets all located in the same business district. Conversely, a business district may include such a large variety of tenants (in terms of sectors) that diversification is achieved in a single geographic location with a limited number of assets. Industry practitioners (see MSCI (2017)) also view the number of real estate assets (from which our Asset Diversification attribute is constructed) as a relevant metric to assess diversification effects and construct portfolios, while also highlighting that the heterogeneity of assets (and markets) needs to be factored into the analysis. Again, an in-depth analysis of SCPIs' financial statements and portfolio composition should support the design of a comprehensive selection process.

5.2.6 Asset Size attribute

The Asset Size attribute discriminates between SCPIs based on the average size of the assets held by each SCPI, that is the ratio $\frac{AUM}{\# \text{ of assets held}}$.

This metric could also be seen as the inverse of the Asset Diversification metric (used in the previous section) normalised by the size of the SCPI. The ratio is computed as of 2019, similarly to the previous section.

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

The 4 equally-sized groups created by the 4 quartiles of the distribution of the $\frac{AUM}{\# \text{ of assets held}}$ ratio are called: 'Low Asset Size', 'Medium Low Asset Size', 'Medium High Asset Size' and 'High Asset Size'.

The results are presented in Exhibits 30 and 31.

Exhibit 30 shows a moderate level of dispersion in performance, with 'Low Asset Size' being

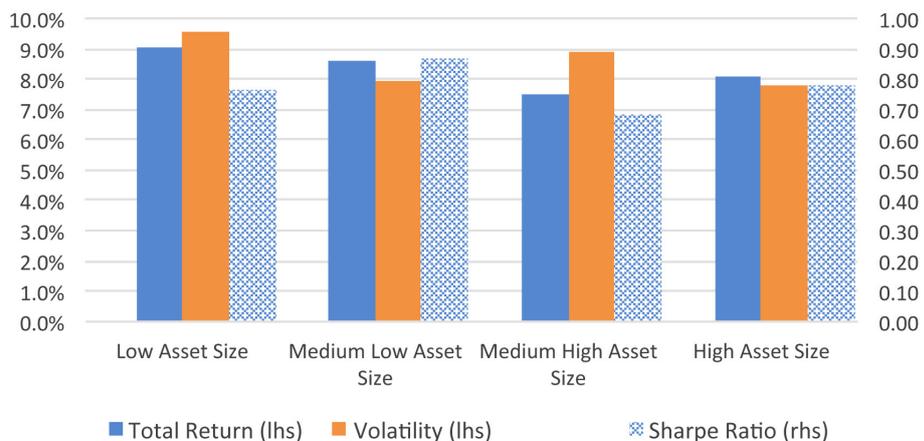
the outperforming group, although our testing indicates the observed differences are not very significant (the p-values respectively associated with the difference between 'Low Asset Size' vs 'Medium High Asset Size', and 'Low Asset Size' vs 'High Asset Size' are 15% and 28%). Additionally, Exhibit 31 does not highlight any particularly strong effect in risk (volatility) or risk-adjusted return (Sharpe ratio). On this basis, we do not propose to include the Asset Size attribute in the

Exhibit 30: Total return performance of the group portfolios relating to the Asset Size attribute from 2003 to 2019



Notes: Each portfolio is rebased at 100 as of 31 December 2003 and grows at the total return rate. The solid blue (respectively orange, grey, and yellow) line represents the evolution of the value of the 'Low Asset Size' (respectively 'Medium Low Asset Size', 'Medium High Asset Size' and 'High Asset Size') portfolio.

Exhibit 31: Cross-sectional averages of total return, volatility and Sharpe ratio for the groups relating to the Asset Size attribute (2003–2019)



Notes: For each group we compute, for the 2003–2019 period, the cross-sectional average of the time-series average annual (log-) total returns, the cross-sectional average of the annual volatility estimate of total returns (incorporating statistical treatments for smoothing and infrequent data), and the cross-sectional average of ex-post Sharpe ratio of total returns. The blue and orange bars (lhs y-axis) respectively represent the average total return and the average volatility, while the pattern-filled bars (rhs y-axis) represent the average Sharpe ratios.

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

selection process. It is worth noting that academic research has observed a positive effect of large property size on returns and risk-adjusted returns and has provided several explanations for this (see Seiler et al. (1999) for details). One possible explanation is that large property assets create the potential for economies of scale and therefore proportionally reduce the costs of managing those assets. Also, larger assets are less liquid and therefore compensate owners with a liquidity premium. Finally, larger properties often contain a greater number of tenants, thus reducing vacancy risk. Industry publications have also reported an outperformance of large properties. Using direct commercial real estate investment data, Reid (2017b) observes that *large* US office assets (worth more than \$200m) outperformed (in terms of annual total return) *small* US office assets in 17 of the 18 years from 1999 to 2016.

To conclude, we note that the 'Low Asset Size' group partially overlaps with the 'Retail' group. Retail SCPIs tend to hold smaller assets than their Office counterparts. For example, 60% of the 'Low Asset Size' group (8 SCPIs out of 13) comprise

Retail SCPIs, which compares with only 23% of Retail SCPIs in our dataset (12 out of 53). This is consistent with the brick-and-mortar/high street strategy pursued by Retail SCPIs, partly a result of the historical scarcity of large shopping centres in France.

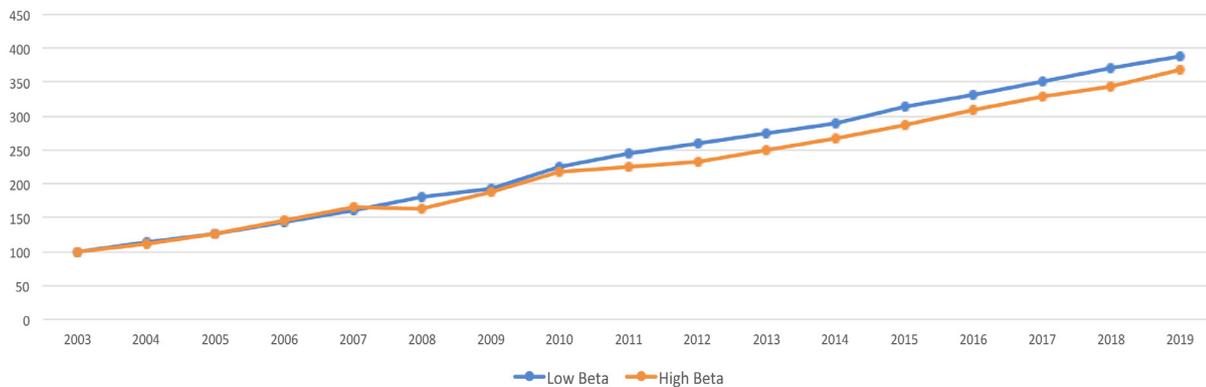
5.2.7 Market Beta Attribute

Our Market Beta attribute relies on the market model described in Section 3.4. More specifically, the SCPIs that have a statistically significant "beta" or slope coefficient "b" in our simple market model defined in Section 3.4.3 (equation (3)) (representing approximately half of the population as per Section 3.4.5) will fall into a 'High Beta' group, while the others will be the members of the 'Low Beta' group.

The results are presented in Exhibits 32 and 33.

Exhibit 32 shows that the two portfolios have a similar performance in terms of total returns during the 2003–2019 period: respectively 8.5% and 8.1% average annual total return for the 'Low Beta' and 'High Beta' portfolios.

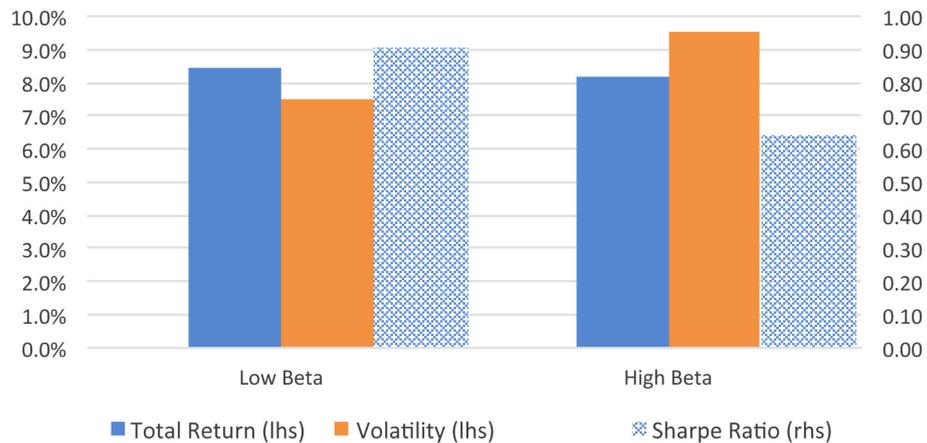
Exhibit 32: Total return performance of the group portfolios relating to the Market beta attribute from 2003 to 2019



Notes: Each portfolio is rebased at 100 as of 31 December 2003 and grows at the total return rate. The solid blue (respectively orange) line represents the evolution of the value of the 'Low Beta' (respectively 'High Beta') portfolio.

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

Exhibit 33: Cross-sectional averages of total return, volatility and Sharpe ratio for the groups relating to the Market beta attribute (2003–2019)



Notes: For each group we compute, for the 2003–2019 period, the cross-sectional average of the time-series average annual (log-) total returns, the cross-sectional average of the annual volatility estimate of total returns (incorporating statistical treatments for smoothing and infrequent data), and the cross-sectional average of ex-post Sharpe ratio of total returns. The blue and orange bars (lhs y-axis) respectively represent the average total return and the average volatility, while the pattern-filled bars (rhs y-axis) represent the average Sharpe ratios.

The difference in annual return of 0.4% is not statistically significant according to our analysis (p -value = 55%). However, we see in Exhibit 33 that the average volatility of each group is materially different: 7.5% for the 'Low Beta' portfolio and 9.5% for the 'High Beta' portfolio. The large difference in Sharpe Ratios is a natural consequence of this discrepancy in volatility.

This result might be puzzling for traditional equity investors because idiosyncratic risk is generally assumed not to be compensated in equity markets. Put another way, an equity investor would have expected 'Low Beta' SCPIs to deliver a lower return along with the (expected) lower volatility. However, this is less surprising for the real estate asset class, where idiosyncratic risk cannot easily be diversified away (in part due to indivisibility and the need for day-to-day property management) and is therefore priced by the market. See Ooi et al. (2009) for a study of this effect on US REITs. The value of the

Market Beta attribute, if any, therefore lies in its discriminating power in terms of risk-adjusted return. Interestingly, such discriminating power does not seem to overlap with that of the Volatility attribute, since the probability of an SCPI belonging to the 'Low Beta' group (respectively the 'High Beta' group) conditional upon belonging to either the 'Low Vol' or 'Medium Low Vol' group is equal to 54% (respectively 56%). This compares with an unconditional probability of being 'Low Beta' (respectively 'High Beta') equal to 49% (respectively 51%). However, the design of the Market Beta attribute could be affected by misspecification (the high or low nature of the "beta" is naturally model-dependent) and the same in-sample issues (since "beta" is known ex-post only) mentioned for the Volatility attribute (see Section 5.2.4). Therefore, we again recommend out-of-sample testing to assess the robustness of the attribute and possibly improve its design before including it in a selection process.

5. Cross-Sectional Attributes of the SCPI Universe and Benefits of Selection

5.2.8 Past Performance Attribute

While full out-of-sample testing of selection decisions is beyond the scope of this paper, we nevertheless analyse a Past Performance attribute in this section, with the aim of assessing whether strong past performance is any predictor of future performance for a given SCPI. For this purpose, we divide our dataset into two equal periods: period 1 goes from 2003 to 2011 and period 2 goes from 2011 to 2019. We create three groups of SCPIs based on their total return performance in period 1: a member of the top quartile is deemed a 'strong performer in period 1', a member of the bottom quartile is deemed a 'poor performer in period 1', and the members of the two remaining quartiles are 'medium performers in period 1'.

In Exhibit 34 we compute empirical transition probabilities by looking at the total return performance of the members of each group during period 2.

We then examine whether the observed transition probabilities deviate from the values that would in theory prevail in the absence of any performance persistence (if future performance was unpredictable). The results in Exhibit 34 indicate a level of persistence that is modest at best. The probability of being a strong performer in period 2 conditional on being a strong performer

in period 1 is 38% (highlighted in green), materially above the theoretical level of 25% (the corresponding unconditional probability) one would expect if performance was fully unpredictable. Similarly, poor performers in period 1 tend to remain poor performers in period 2, with a transition probability of 31% (highlighted in green) slightly above the 25% threshold. However, strong performers in period 1 also have an abnormal probability of performing poorly in period 2, judging by the 31% probability (highlighted in orange) in the top right-hand corner of Exhibit 34. Strong performance in period 1 apparently also creates more volatility in period 2. The predictive power of poor performance in period 1 seems more straightforward: only 15% of poor performers in period 1 end up performing strongly in period 2. We therefore consider a strategy of *excluding* the poor performers of period 1, or equivalently selecting SCPIs that are *either* strong or medium performers in period 1. This strategy leads to a 27.5% probability of selecting an SCPI that performs strongly in period 2 and a 22.5% probability of selecting one that performs poorly in period 2. In conclusion, the results above show a modest level of persistence in total returns over a long-term horizon. Further out-of-sample research will therefore be required for investors to opine on the inclusion of a past performance attribute in their selection process.

Exhibit 34: Empirical transition probabilities between 2003–2011 and 2011–2019 performance regimes

	Strong performer in period 2	Medium performer in period 2	Poor performer in period 2
Strong performer in period 1	38% (uncond.prob. = 25%)	31% (uncond.prob. = 50%)	31% (uncond.prob. = 25%)
Medium performer in period 1	22% (uncond.prob. = 25%)	59% (uncond.prob. = 50%)	19% (uncond.prob. = 25%)
Poor performer in period 1	15% (uncond.prob. = 25%)	54% (uncond.prob. = 50%)	31% (uncond.prob. = 25%)

Notes: The table shows the probability for a given SCPI of being amongst the strong, medium or poor performers during the 2011–2019 period conditional on being a strong, medium or poor performer during the 2003–2011 period. For example, a medium performer in 2003–2011 has a 59% probability of remaining a medium performer in 2011–2019. Below each conditional probability, the corresponding unconditional probability is indicated in parentheses.

6. Portfolio Diversification and Benefits of Allocation

6. Portfolio Diversification and Benefits of Allocation

In Section 3 we highlighted the levels of performance and risk dispersion within the universe of SCPIs and argued that such dispersion was conducive to the implementation of fund selection and portfolio allocation. In Section 4 we identified three specific SCPI attributes that could plausibly explain the cross-sectional differences in risk and return to demonstrate the benefits of a selection process for SCPI investors.

In this section we complete the exercise by assessing the effects of diversification in SCPI portfolios. This should in turn help us reach conclusions about the relevance and possible benefits of a portfolio allocation process when investing in SCPIs.

As mentioned in Seiler et al. (1999), both academics and practitioners have acknowledged the benefits of diversification within the real estate class. Real estate diversification is most commonly considered across property types, across geographic regions (this has led to the concept of economic regions, viewed as more homogeneous than purely geographic regions), and across metropolitan zones (i.e. urban versus suburban zones).

We argue that the SCPI market is diverse enough to facilitate all three types of diversification. Indeed, SCPI investors can choose from the Office, Retail and Specialised asset categories to allocate across property types. Furthermore, the SCPI market actually provides "pre-packaged diversification" in this respect, in the form of Diversified SCPIs. Additionally, the SCPI market offers exposure to a wide range of geographic regions and metropolitan zones as evidenced by

the geographic breakdown of the SCPI portfolios at the end of 2018 (see Schoeffler (2020)): Paris (20%), Paris region (40%), France ex-Paris region (28%), and Europe ex-France (12%). Therefore, we argue that an Equally-Weighted (EW) portfolio of SCPIs would in fact capture all three types of diversification available in the SCPI market. Also, to the extent that idiosyncratic risk is a large component of an SCPI's total risk (see sections 2.4.5 and 4.1.7), we naturally expect to see this is via improved risk-adjusted returns of the EW portfolio.

The first part of this section is an analysis of the risk and return profile of the EW portfolio of all 53 SCPIs in our dataset. We construct the EW portfolio as a static portfolio, without any rebalancing throughout the investment period, thus avoiding implementation issues that may arise as a result of the low liquidity and the transaction costs associated with SCPIs. The second part further analyses the impact of the number of SCPIs on a portfolio's risk-adjusted returns, effectively quantifying the "speed" at which diversification effects become visible. The third part compares the EW portfolio with other commonly used market-wide portfolios and concludes on the benefits of diversification within the SCPI universe. The final part briefly discusses possible limits to the benefits diversification when introducing the relative lack of liquidity of SCPIs.

6.1 Risk and Return Profile of the Equally-Weighted (EW) Portfolio

We compute the following return and risk metrics for the EW portfolio for the 2003–2019 period and compare them to the universe of individual

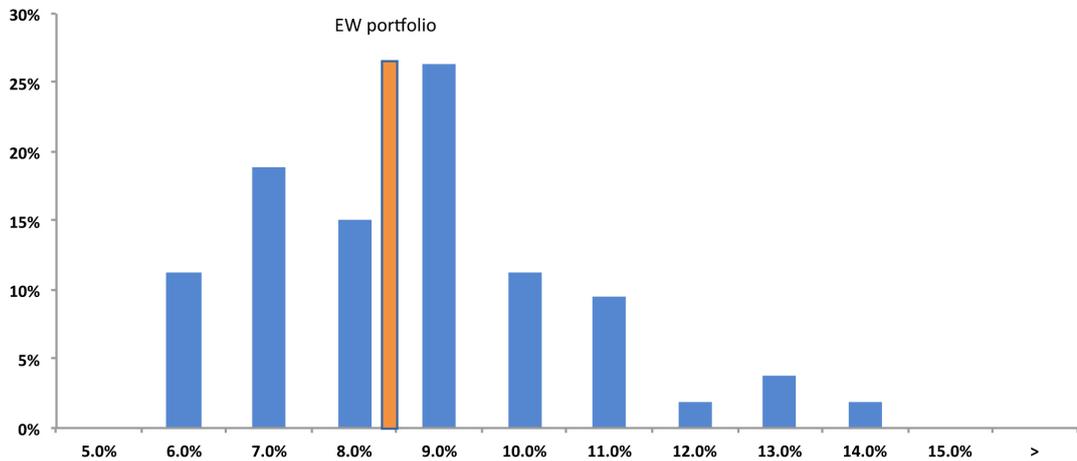
6. Portfolio Diversification and Benefits of Allocation

SCPIs: average total return, average dividend yield, total return volatility, dividend yield volatility and Sharpe ratio. We present the results respectively in Exhibits 35, 36, 37, 38 and 39.

By construction, the annual total return of the EW portfolio is equal to the mean of the cross-sectional distribution, in this case 8.3%. The

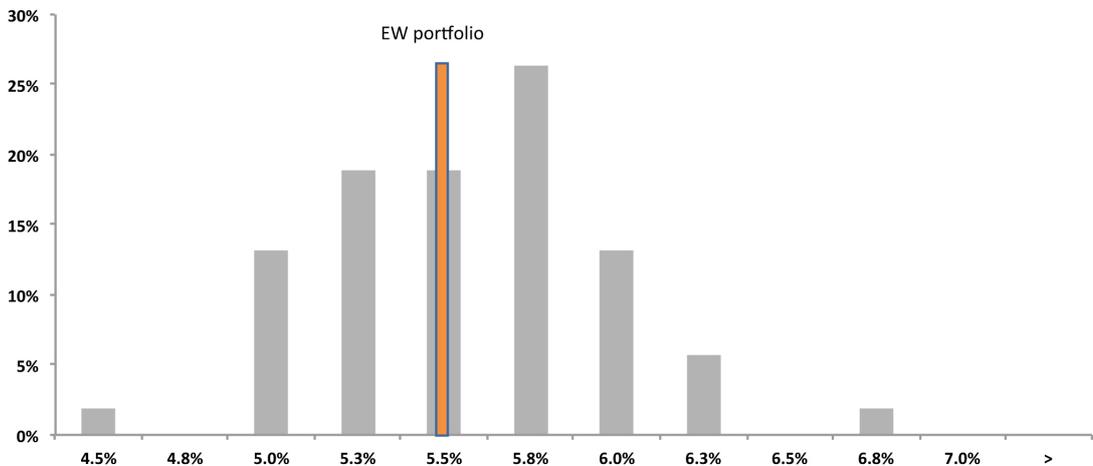
median of the total return distribution is 8.2%, very close to the mean, which implies that the EW portfolio outperforms (and underperforms) roughly half the population of SCPIs in terms of total return. This is visible in Exhibit 35, which shows that the total return performance of the EW portfolio is "as good as the average SCPI in the portfolio".

Exhibit 35: Annual total return of the EW portfolio compared to the cross-sectional distribution of SCPIs' annual total returns (2003–2019 averages)



Notes: We use the histogram presented in Exhibit 13 (blue bars) and overlay the 2003–2019 average of annual (log-) total returns for the EW portfolio (orange bar).

Exhibit 36: Annual dividend yield of the EW portfolio compared to the cross-sectional distribution of annual dividend yields (2003–2019 averages)



Notes: We use the histogram presented in Exhibit 15 (grey bars) and overlay the 2003–2019 average of annual dividend yields for the EW portfolio (orange bar).

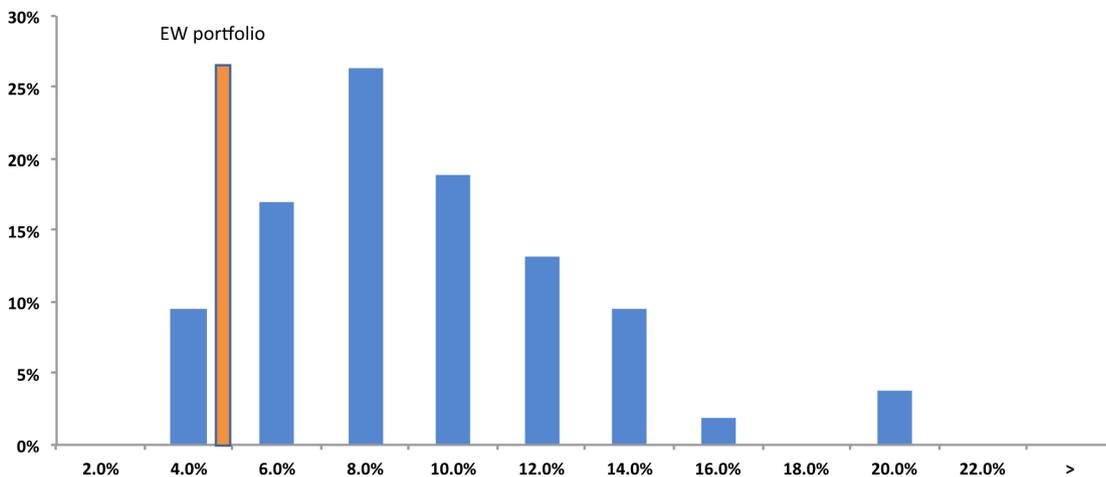
6. Portfolio Diversification and Benefits of Allocation

Exhibit 36 shows that the same conclusion can be reached with respect to the yield generated by the EW portfolio. By construction, the annual dividend yield of the EW portfolio is equal to the mean of the cross-sectional distribution, in this case 5.45%. The median of the dividend yield distribution is 5.47%, very close to the mean, which implies that the EW portfolio outperforms

(and underperforms) roughly half the population of SCPIs in terms of dividend yield.

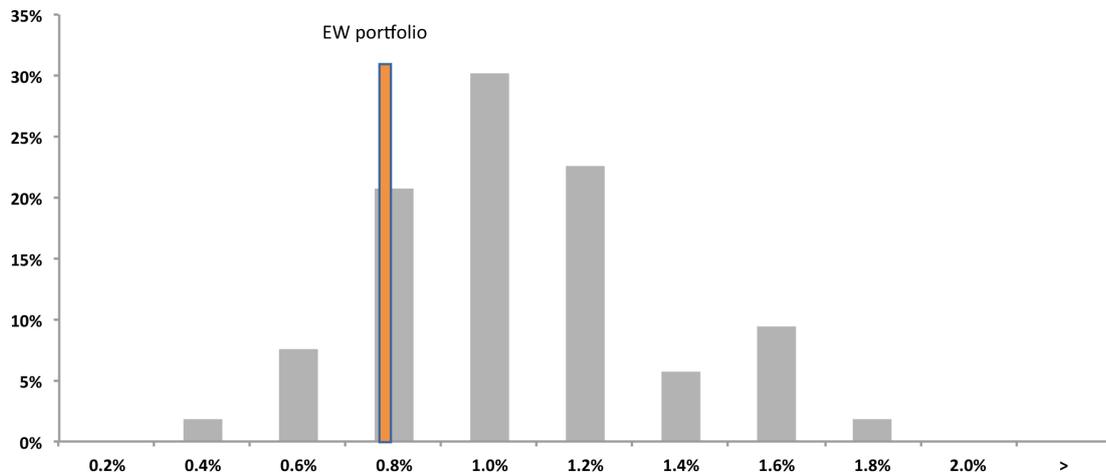
The annual volatility of the total return of the EW portfolio is 4.7%. As expected, this is significantly lower than the average volatility across the SCPI universe (8.5%) and is also lower than the volatility of total returns achieved by 88% of the

Exhibit 37: Annual total return volatility of the EW portfolio compared to the cross-sectional distribution of annual total return volatilities (2003–2019)



Notes: We use the histogram presented in Exhibit 16 (blue bars) and overlay the 2003–2019 annual total return volatility of the EW portfolio (orange bar).

Exhibit 38: Annual dividend yield volatility of the EW portfolio compared to the cross-sectional distribution of annual dividend yield volatilities (2003–2019)



Notes: We use the histogram presented in Exhibit 18 (grey bars) and overlay the 2003–2019 annual dividend yield volatility of the EW portfolio (orange bar).

6. Portfolio Diversification and Benefits of Allocation

population of SCPIs in our dataset. This is strong evidence of the risk reduction benefits expected from diversification for SCPI investors.

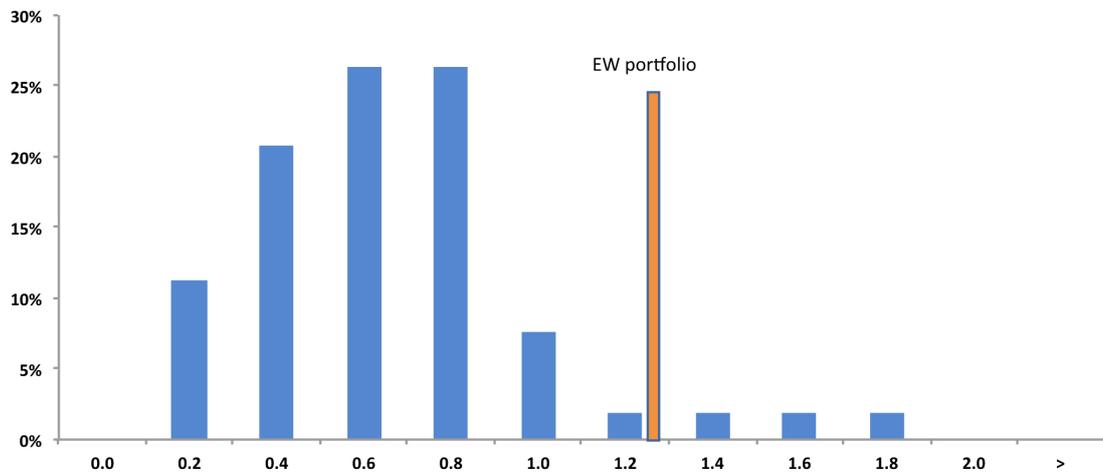
Note that some of the attribute-related group portfolios in Section 4, such as the 'Low Vol' or the 'Low Beta' portfolios, are less volatile than the EW portfolio despite having fewer SCPI constituents. This is likely explained by the in-sample (ex-post) nature of these portfolios, meaning one needs to know the realised performance of each SCPI throughout the period to determine whether it belongs to the 'Low Vol' or 'Low Beta' group. On the other hand, constructing the EW portfolio requires no knowledge of the future behaviour of every SCPI.

The annual volatility of the dividend yield of the EW portfolio is 0.78%. This is lower than the average volatility of dividend yield across the SCPI universe (0.96%) and is also lower than the dividend yield volatility of 75% of the SCPI population. The discount observed is

less significant than in the case of total return volatility because it is dispersion that drives the benefit of diversification, and we know from Section 3.2 that the dispersion in dividend yield volatilities is much smaller than it is for total return volatilities.

We conclude by reviewing the ex-post Sharpe ratio of total returns of the EW portfolio, equal to 1.24 (see Exhibit 39). It is materially higher than the average Sharpe ratio of 0.77 across the SCPI population (as well as the median Sharpe ratio of 0.71), as a direct consequence of the sizeable reduction in volatility observed in Exhibit 37, combined with a performance that remains in line with the "average SCPI of the portfolio" as observed in Exhibit 35. More specifically, the EW portfolio dominates about 92% of the SCPI population in terms of Sharpe ratio, again showing the "free lunch" provided by diversification.

Exhibit 39: Ex-post Sharpe ratio of the EW portfolio total returns compared to the cross-sectional distribution of ex-post Sharpe ratios total returns (2003–2019)



Notes: We use the histogram presented in Exhibit 19 (blue bars) and overlay the 2003–2019 ex-post Sharpe ratio of the EW portfolio total returns (orange bar).

6. Portfolio Diversification and Benefits of Allocation

6.2 Impact of the Number of SCPIs on a Portfolio's Risk-Adjusted Return

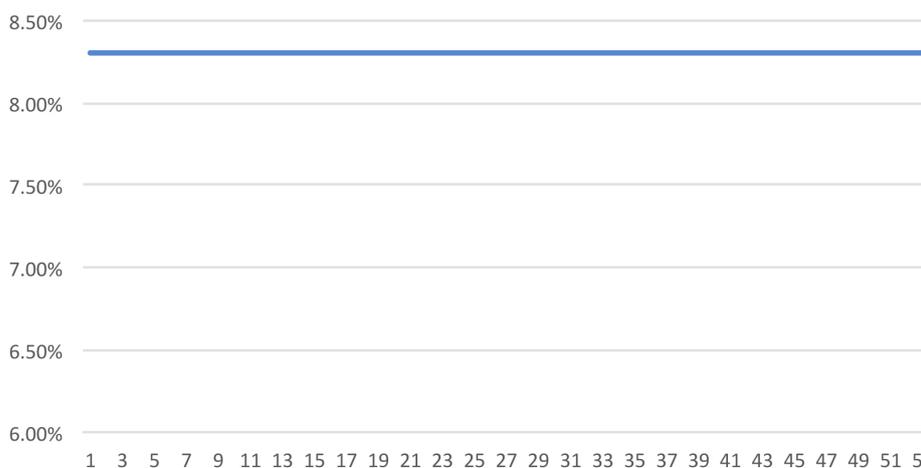
Although the EW portfolio features an attractive risk and return profile due to strong diversification benefits, it may often be difficult or impractical for an investor to implement and manage such a large portfolio (see also Section 6.4). Our goal in this section is therefore to analyse how quickly the diversification effect starts impacting risk-adjusted returns when an investor grows the number of SCPIs in her portfolio. To this end, we have constructed random portfolios with a gradually increasing number of SCPIs and have examined the average risk and return characteristics of these random portfolios as a function of their size (i.e. the number of SCPIs in them).

More specifically, we assign an integer from 1 to 53 to each of 53 SCPIs analysed in our dataset and then generate 2,000 random permutations of the set of integers $\{1, \dots, 53\}$. Each permutation can be represented as a series (p_i) where

$$\begin{aligned}
 & i = 1, \dots, 53 \\
 & 1 \leq p_i \leq 53 \\
 & p_i \neq p_j \text{ if } i \neq j
 \end{aligned}$$

For every permutation, a random equally-weighted portfolio comprising k SCPIs ($1 \leq k \leq 53$) can be constructed by combining the SCPIs numbered p_1, p_2, \dots, p_k . Obviously, for k equal to 1 (or 52) there are only 53 possible single-asset (or 52-asset) SCPI portfolios, and for k equal to 53 there is only one possible portfolio, namely the EW portfolio. Then, for each random portfolio we compute the 2003–2019 average annual total return and the 2003–2019 annual volatility of total return. Finally, we group together random portfolios of equal size k and compute an average total return and an average volatility for each group to estimate (1) a *return* metric, namely the expected 2003–2019 average total return and (2) a *risk* metric, namely the expected 2003–2019 annual volatility, for a randomly constructed portfolio of k SCPIs.

Exhibit 40: Expected annual total return of a random equally-weighted SCPI portfolio as a function of the number of SCPIs comprising the portfolio



Notes: The solid blue line represents the expected 2003–2019 average annual total return of a randomly constructed equally-weighted portfolio of k SCPIs as a function of $k = 1, \dots, 53$. The expected value is obtained by computing the mean of the 2003–2019 average annual total returns across 2,000 random portfolios of size k .

6. Portfolio Diversification and Benefits of Allocation

Exhibit 40 displays the evolution of the return metric when k , the number of SCPIs, increases from 1 to 53. As expected, we see that increasing the number of SCPIs in the portfolio does not affect the average total return over the 2003–2019 period (we assume no market friction; see Section 6.4 for further considerations on liquidity). Put another way, adding an extra SCPI to the portfolio leads, on average, to the same total return over the 2003–2019 period.

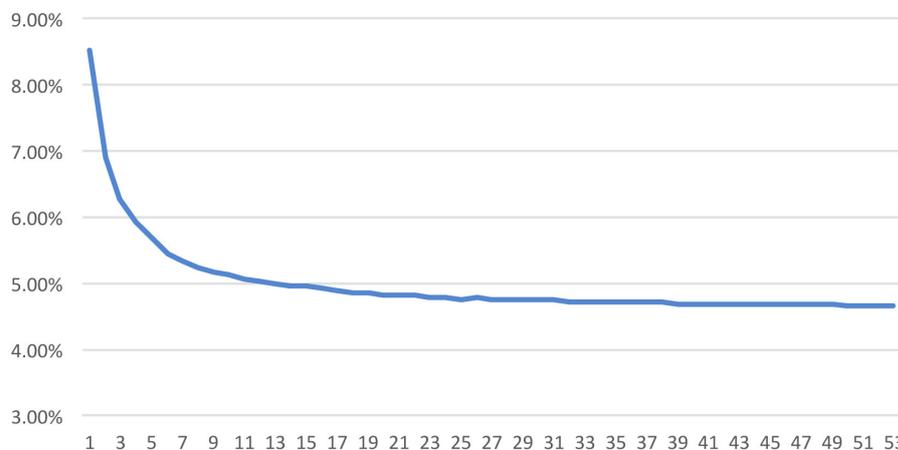
Exhibit 41 shows the evolution of the risk metric when k increases from 1 to 53. Unlike the return metric case, we observe that increasing the number of SCPIs in the portfolio very much affects its expected total return volatility. This is a natural consequence of the (total return) correlation between SCPIs being materially less than 100% for most pairs (see Section 3.4.5). Adding an extra SCPI to the portfolio is therefore, on average, risk-reducing and the benefits are very strong at the beginning (low values of k) and gradually lessen as the number of SCPIs in the

portfolio grows. Based on our dataset, it appears that an equally weighted portfolio of 15 SCPIs is, on average, already capturing more than 90% of the risk reduction one would obtain via the full EW portfolio of 53 SCPIs. This is a promising feature for investors deciding to incorporate selection decisions into their investment process. Indeed, it indicates that selecting 15 SCPIs out of 53, i.e. eliminating over 70% of the population, does not substantially reduce the benefits of portfolio allocation for investors.

6.3 Comparing the EW Portfolio with other Diversification Schemes

The EW portfolio is an intuitive diversification technique, but it is not the only way of achieving diversification. Other schemes have been used by investors in other asset classes. We now compare the EW approach to three other simple schemes commonly used in the equity world, namely the Capitalisation-Weighted (CW) approach, the Global Minimum-Variance (GMV) approach and the Inverse Volatility-Weighted (IVW) approach.

Exhibit 41: Expected annual total return volatility of a random equally-weighted SCPI portfolio as a function of the number of SCPIs comprising the portfolio



Notes: The solid blue line represents the expected 2003–2019 annual total return volatility of a randomly constructed equally-weighted portfolio of k SCPIs as a function of $k = 1, \dots, 53$. The expected value is obtained by computing the mean of the 2003–2019 annual total return volatilities across 2,000 random portfolios of size k .

6. Portfolio Diversification and Benefits of Allocation

The CW portfolio is self-explanatory: each SCPI is weighted in accordance with its AUM, so the larger the SCPI's AUM, the larger its weight. This is an ex-ante scheme because the capitalisation is known at the time of investment and no forward-looking information is required to compute the weights. For the purpose of our analysis, we determine the weights of the CW portfolio using the average annual (year-end) AUM between 2003 and 2019.

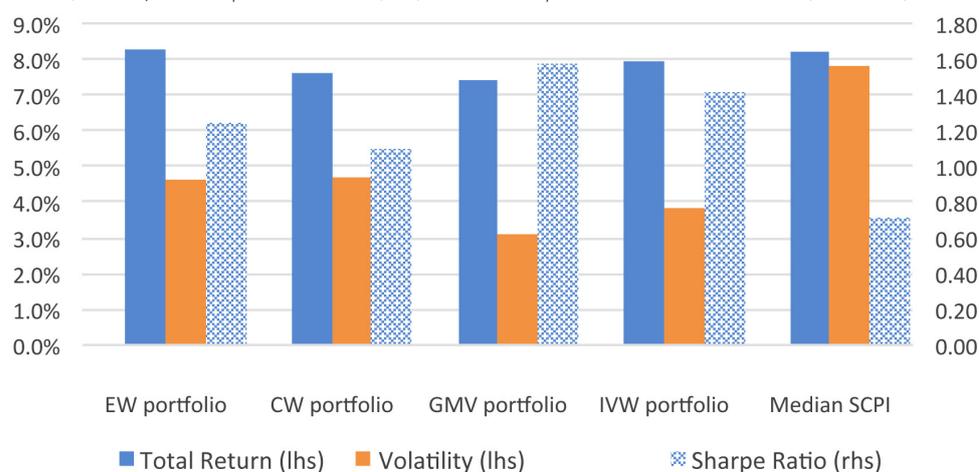
The GMV portfolio is the optimal portfolio selected by mean-variance investors that do not wish to target a specific expected return. As the name indicates, it is the efficient portfolio with the lowest variance and its construction does not require knowledge of future expected returns, which are typically subject to large estimation errors. It does however require knowledge of future variances and covariances of returns. When implemented "in-sample" (our intention here), it is prone to overfitting issues, because variances and covariances are known with certainty at the time

of investment. To mitigate this effect, we impose a minimum weight of $1/2N$ (and a maximum weight of 100%), where N is the number of SCPIs considered (53) to constrain the minimisation of portfolio variance.

The IVW portfolio is defined as the portfolio where each SCPI has a weight proportional to the inverse of its volatility. It may be viewed as a special case of an equal risk contribution portfolio where the correlation between the returns is assumed to be constant across all pairs of constituents. Its computation requires knowledge of future variances.

In order to analyse potential differences in risk and return profile induced by the four weighting schemes (EW, CW, GMV and IVW), we compute three metrics for each portfolio (the time-series average annual total return, the time-series volatility of total return and the ex-post Sharpe ratio) and represent the results in Exhibit 42.

Exhibit 42: Total return, volatility and Sharpe ratio of the EW, CW, GMV and IVW portfolios and the Median SCPI (2003–2019)



Notes: For each diversified portfolio we compute, for the 2003–2019 period, the average of annual (log-) total returns, the annual volatility estimate of total returns (incorporating statistical treatments for smoothing and infrequent data), and the ex-post Sharpe ratio of total returns. The Median SCPI represents the cross-sectional median values of total return, volatility, and Sharpe ratio across the SCPI universe. The blue and orange bars (lhs y-axis) respectively represent the average total return and the volatility, while the pattern-filled bars (rhs y-axis) represent the Sharpe ratios.

6. Portfolio Diversification and Benefits of Allocation

We first focus on the risk metric, namely the volatility of each portfolio, and observe that all four weighting schemes lead to substantial risk reduction compared to the Median SCPI in the dataset. This is reassuring and is supporting evidence that allocation decisions can add value for investors independently of the allocation technique implemented. We note that the risk reductions (vs the Median SCPI) generated by the GMV and IVW schemes (respectively 60% and 51% reduction in volatility) are larger than those generated by the EW and CW schemes (40% for both schemes). As explained earlier, this is likely due to the ex-post nature of the scheme in the context of an “in-sample” analysis (akin to a hypothetical benefit of hindsight when constructing the portfolio). When implemented “out-of-sample”, the superiority of the GMV portfolio compared to the EW portfolio is less obvious (see DeMiguel et al. (2009)) but it remains a commonly used scheme nevertheless. In practice, we expect the relative scarcity of data for SCPIs (and the estimation errors associated with variances and covariances of SCPI returns) to remain a constraint for the implementation of the GMV and IVW portfolios.

Turning to performance, Exhibit 42 shows that the time-series average total return for each of the four diversified portfolios (respectively 8.3%, 7.6%, 7.4% and 7.9% for EW, CW, GMV and IVW) is largely in line with that of the Median SCPI (8.2%) despite the substantial reduction in risk. Based on the hypothesis-testing framework proposed in Section 5.1, the respective differences in total returns of +0.1%, -0.6%, -0.8% and -0.3% are not statistically significant (p-values in excess of 45%, largely driven by the total

return volatility of one single SCPI). The absence of material impact on returns combined with a substantial risk reduction is very consistent with the simulated results displayed in Section 6.2. We also analyse the differences in total return across the four diversified portfolios. In particular, the EW portfolio seems to outperform the CW and GMV portfolios. We leave the latter aside because of possible in-sample biases and focus on the EW and CW schemes, which are both ex-ante in nature. Again, based on the hypothesis-testing framework proposed in Section 5.1, we compute a p-value of 10% to reject the null hypothesis of equal mean returns for the two portfolios. The p-value obtained urges caution but hints at the possibility of a genuine difference in expected returns caused by the weighting scheme. The underperformance of the CW portfolio versus the EW portfolio is a common observation in the equity asset class and is explained by the implicit exposure of the CW portfolio to poorly compensated equity risk factors. The academic literature on REITs has investigated this topic and has found the presence of risk factors linked to Value and Size (see Guidolin and Pedio (2019)). On the practitioners' side, S&P Dow Jones Indices launched the S&P 500 Equal Weight Real Estate Index in 2015 in order to offer a REIT “smart beta” solution. However, the non-listed nature of SCPIs most likely requires a dedicated strand of research to identify relevant risk factors and confirm the exact nature of the risk premia collected by SCPI investors. This would in turn inform the choice between the EW and the CW portfolio, and possibly other weighting schemes.

6. Portfolio Diversification and Benefits of Allocation

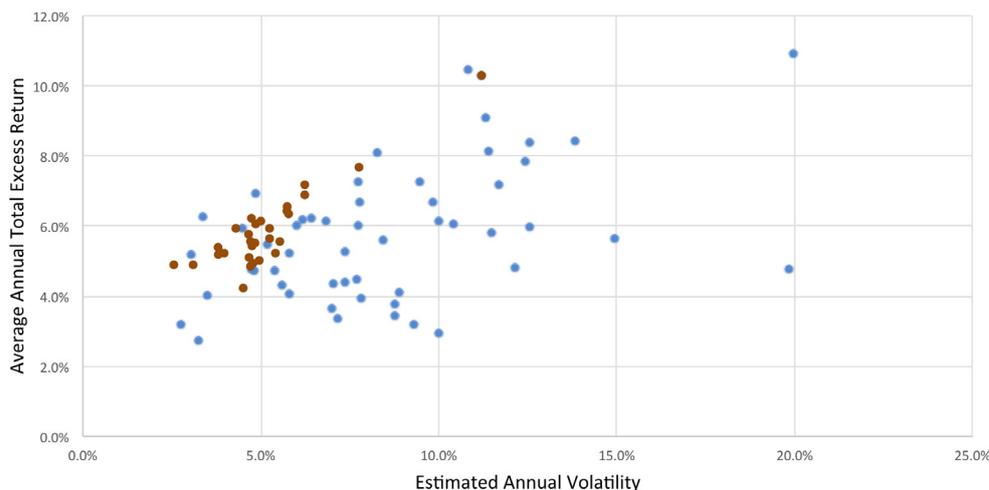
Finally, as expected, Exhibit 42 shows that the four diversification schemes materially outperform the Median SCPI from a risk-adjusted returns standpoint, highlighting the material benefits of allocation for SCPI investors. To conclude, given the strong improvements in risk (and risk-adjusted returns) achieved by all four methods, we would argue that the choice of the exact diversification scheme matters less than the decision to consider allocation as an integral part of the investment decision process in SCPIs. And since a picture is often said to be worth a thousand words, we close this section with a classical risk-return map (see Exhibit 43) of all the SCPI portfolios we analysed in our paper, plotting their average annual total excess return (y-axis) versus their estimated annual volatility (x-axis). The blue points on the map are individual SCPIs (i.e. single-asset portfolios) while the brown points are multi-SCPI portfolios. It seems clear that the brown points are overwhelmingly to the left of the

blue points, evidence that diversification across SCPIs can generate enhanced risk and return profiles. The blue points that stubbornly remain to the left of brown points might be pointing to potential reserves of untapped efficiency, or more realistically to estimation errors.

6.4 Liquidity Constraints and Limits to Diversification

Our analysis so far has shown the tangible benefits of diversification applied to SCPI investments. We have not, however, exhaustively reviewed the challenges or constraints faced by an SCPI investor looking to implement allocation decisions as part of her investment process. Such a review is beyond the scope of this paper, but we would like to briefly discuss one particular constraint which we find is somewhat specific to the SCPI asset class, namely liquidity.

Exhibit 43: Map of total excess returns against volatility for all 53 SCPIs in the dataset and all SCPI portfolios analysed in the paper (2003–2019 estimates)



Notes: For each SCPI or each portfolio we compute, for the 2003–2019 period, the average of annual (log-) total excess returns, and the annual volatility estimate of total returns (incorporating statistical treatments for smoothing and infrequent data). The Risk-Free rate used to compute excess returns is the average of the 10y French OAT yield over the 2003–2019 period (equal to 2.52%). The blue points are individual SCPIs, the brown points are SCPI portfolios.

6. Portfolio Diversification and Benefits of Allocation

As mentioned in Section 2, secondary market volumes of SCPIs are low compared to listed REITs and SCPI investors face potentially sizeable “bid-offer” spreads in the form of subscription fees. It is therefore possible that diversification comes at a cost, and investors may need to consider the tangible benefits of allocation as part of a trade-off. Let us consider two practical examples, one for a private investor and one for a larger institutional investor.

A private investor currently holds two SCPIs in her investment portfolio and has identified several other SCPIs she wishes to include in her portfolio to enhance her risk-adjusted returns. Unless she has unused capital to deploy, she will need to sell a portion of her current holdings in order to purchase the new SCPI shares and will thus incur a sizeable bid-offer cost (by effectively crystallising the subscription fees on the sold SCPI shares). The decision to diversify or not is therefore the result of a trade-off: the marginal enhancement in risk-adjusted returns needs to overcompensate for the bid-offer cost.

A large institutional investor may face an additional constraint when it comes to diversification (bid-offer costs clearly remain an important factor but they are significantly lower, typically around 1%, for institutional investors). Indeed, the ability to rebalance a portfolio in the face of market changes or to monetise a position is potentially impacted by the size of the investment. An institutional investor looking to build up a diversified portfolio of SCPIs therefore needs to size each position appropriately in order to maintain some minimum level of liquidity for the portfolio as a whole. This may very well mean

significantly reducing exposure to (or possibly excluding) some well-diversifying SCPIs because their secondary market volumes are deemed insufficient. The allocation decision is again the result of a trade-off between the diversification benefits and the potential cost of the liquidity risk associated with a diversifying position.

6. Portfolio Diversification and Benefits of Allocation

7. Conclusion

7. Conclusion

Publicly registered non-listed real estate investment vehicles aim to strike a balance between liquidity (typically available in REITs) and decorrelation from traditional asset classes (typically observed in direct real estate investments), in order to give the best of both worlds to investors. The regulated French investment vehicle known as *Société Civile de Placement Immobilier* (SCPI) has been operating with this ambitious goal in mind since the 1960s. The SCPI market has experienced double-digit growth in assets under management over the past decade and has initiated a trend towards differentiation and dispersion that help cater for the needs of investors. Such dispersion is also an opportunity for SCPI investors to consider some of the traditional investment management techniques commonly implemented in the equity asset class. This paper makes the case that substantial benefits could be reaped by making *selection* and *allocation* decisions when investing in SCPIs.

Our study shows a large level of cross-sectional dispersion in the risk and return characteristics of SCPIs, suggesting that value can be added through selection decisions. We also find several attributes to have a relatively strong explanatory power with respect to such differences in risk and performance. Turning to allocation decisions, we find that a portfolio of SCPIs exhibits a level of volatility substantially lower than the average volatility within the universe. We also observe that the choice of weighting scheme does not substantially affect the material risk-reduction benefits of portfolio diversification. As far as the equally-weighted (EW) approach is concerned, we find that 15 SCPIs are enough to capture over 90% of the diversification benefits, paving

the way for a combination of value-adding selection and allocation decisions. Overall, our results suggest that an open-architecture multi-management approach to investment in SCPIs would lead to substantial welfare enhancement for investors seeking exposure to the French commercial real estate market.

Our work could be extended in several directions. With regards to selection, the inclusion of financial analysis data (sourced from SCPIs' financial statements and management reports) seems a natural step forward to design an institutional-grade selection process. Future research could for example aim to define robust *pricing* factors that explain the cross-section of expected SCPI returns and can be related to plausible and persistent risk premia. For example, academic research in equities establishes a link between the "value premium" and the level of financial leverage of a corporation. It is possible a similar risk-based logic is at play in a real estate investment fund. If so, the recent increase in leverage observed within the SCPI universe is likely to facilitate the detection of any associated risk premium. With regards to allocation, the identification and/or construction of relevant risk factors explaining the time variations of returns as well as the cross-section of returns (or equivalently the time covariations of returns) will guide investors in their search for material diversification benefits. The aim would be to avoid the risk of "fake" diversification that could occur when combining a large number of SCPIs exposed to the very same risk factors.

These two possible extension routes could then lead to an analysis of the added value of passive and/or active SCPI fund-of-funds solutions, as

7. Conclusion

well as laying the ground for the inclusion of such enhanced SCPI portfolios as part of the performance-seeking and/or liability-hedging portfolios of innovative liability-driven or goal-based investing solutions. We leave these questions for further research.

7. Conclusion

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Asset Managers France

About Swiss Life Asset Managers France

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1 - As at 31/12/2020

2 - The infrastructure management teams are based in Zurich, Switzerland, and report to Swiss Life Asset Managers



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For more information, please contact.
Maud Gauchon on +33 (0)4 93 18 78 87
or by e-mail to. maud.gauchon@edhec-risk.com

EDHEC-Risk Institute
393 promenade des Anglais
BP 3116 - 06202 Nice Cedex 3
France
Tel. +33 (0)4 93 18 78 87

EDHEC Risk Institute—Europe
10 Fleet Place, Ludgate
London EC4M 7RB
United Kingdom
Tel. + 44 207 332 5600

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