KENFO Working Paper

Climate Risk and (Very-)Long-Term Expected Asset Class Returns[1]

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Abstract

We aggregate asset-level data on physical and transition risks in various climate scenarios to be realized by 2050 to assess the implications of yet unpriced climate risk for expected asset class returns and for KENFO's expected overall portfolio return by 2050. Building and calibrating a general equilibrium asset pricing model to derive equilibrium market pricing of – then realized – climate scenarios from 2050 onwards, we also look further ahead and derive (very) long-term expected return implications of climate risk. If we accept the asset-level estimates of physical and transition risks at face value, our findings suggest that depending on the climate scenario which will be realized by 2050, there will be a drag between 10 and 22 basis points on KENFO's expected annual portfolio return until 2050 and a somewhat higher drag between 11 and 27 basis points from 2050 onwards. Differences across scenarios are mainly due to transition risk so that "current policies" scenarios without any transition risk fare better than "net zero" scenarios with orderly transition, and much better than scenarios with delayed and disorderly transition. We also demonstrate that regardless of which scenario we consider, KENFO's current strategic asset allocation entails a lower drag to expected returns until 2050 than KENFO's investible broad market portfolio. Hence, KENFO already addresses climate risk in its strategic asset allocation.

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1 Introduction

Climate change is a major challenge for the century ahead as it entails serious physical risks such as changes in sea level rise, heat waves, increasing weather events, ocean acidification etc. in various regions in the world (Kunreuther et al. (2013)). These changing weather and climate patterns may impact countries and societies in different manners as far as food and water security, infrastructure, health etc. are concerned. Societies need to invest in adaptation and mitigation measures to cope with the current and anticipated impacts of climate change. That process of adapting to climate change for the purpose of mitigating physical risks will require serious political efforts and hence transform societies and business models. Thus, efforts to mitigate climate change entail costs for transitioning to cleaner technologies and sustainable practices (Benedetti et al. (2021)), which, on top of physical risks, implies transition risks and opportunities for businesses.

Investors and academics become increasingly aware of the fact that these physical and transition risks associated with climate change may have serious implications for business performances, and, consequently, investment returns (cf. Antoniuk and Leirvik (2024), França et al. (2023)). Institutional investors already try to mitigate these risks by divesting from single sectors and stocks or integrating backward-looking low-carbon measurements into their investment decisions (Andersson et al. (2016)). In the present paper, by contrast, we take a forward-looking perspective and seek to understand what climate change means for expected returns and how investors can address physical and transition risks in their portfolio construction by means of making climate risk a determinant of their forward-looking return estimates. Given that the strategic asset allocation is the most important determinant of the risk and return portfolios of institutional investors' portfolios (Brinson et al. (1986), Hood (2005)), we focus on the impacts of climate change on expected returns for entire asset classes as required for the derivation of a strategic asset allocation.

As the recent literature survey by Campiglio et al. (2023) demonstrates, there have already been numerous studies which investigate to which extent markets are pricing in climate risk in specific asset classes and how asset class returns might be affected by climate change impacts. These studies focus typically on asset prices, cost of capital, financial risk metrics, and real estate prices in the context of historical emission data and weather events. For example, Bolton and Kacperczyk (2021) suggest that carbon-intensive firms earn higher returns which cannot be explained through differences in size, book-to-market ratio or other return predictors. Capasso et al. (2020) find that higher emissions are related to greater credit risk measured by bond yield spreads and distance-to-default in the context of corporate bonds. Mallucci (2022) demonstrates that extreme weather conditions result in worsened borrowing conditions for Caribbean sovereigns. Rather than focusing on historical climate events and a single asset class as much of that literature, we take an asset owners' multi-asset view and use forward-looking, scenario-based estimates of the impact of climate change on the financial performances of businesses to understand how climate change will affect expected returns on an institutional multi-asset portfolio over the coming decades.

Data providers have recognized the need of investors to assess their exposure to climate risk and the financial implications of such risk and thus increasingly provide tools to assess physical and transition risks in various climate scenarios at the asset level (for an overview of relevant data providers, methodologies and current limitations see UNEP FI (2023)). For the purpose of this paper, we use Blackrock's Aladdin® Climate[2] methodology as our measure of climate risk in order to produce estimates of expected returns which are adjusted for climate risk. The raw data informs us about projected cash flow implications and the associated physical and transitional risks at the corporate or asset level, which we then aggregate to the asset class level to take the perspective of an asset owner with a broadly diversified multi-asset portfolio. Depending on advancements in technology, shifts in geopolitical landscapes, and how aggressively countries and industries act to reduce carbon emissions, climate-related risks for the coming decades can differ significantly. Therefore, the Aladdin Climate methodology comprises different climate models by the Network of Central Banks and Supervisors for Greening the Financial System (NGFS). This includes orderly, disorderly and "hot house world" scenarios, which differ in terms of their levels of both physical and transition risk. In deriving results for such a sufficiently broad range of climate scenarios based on the Aladdin Climate risk data, we follow recommendations by the Task Force on Climate-related Financial Disclosures (TCFD) (cf. TCFD (2022)).

The Aladdin Climate risk data for asset-level cash flows are based on scenarios where yet unpriced climate risk gets priced in by 2050. The dataset models cash-flow implications of climate risk in a given scenario and uses financial models to compute a climate-adjusted valuation metric, which can be thought of as a discounted measure of such unpriced climate risk to the cash flows of the respective asset under current market pricing. Thus, if one is willing to accept that the Aladdin Climate risk data represent an accurate – or at least the best available – estimate of the cash flow implications of climate risk, these climate-adjusted valuation metrics speak quite directly to expected return implications by 2050 for any given asset class once we aggregate the data for all single assets in a benchmark index for an asset class and annualize them. However, in addition to the time horizon from 2023 to

[2] The inclusion of the Aladdin Climate analytics, provided by BlackRock, contained in this report should not be construed as a characterization regarding the materiality or financial impact of that information. The Aladdin Climate analytics include non-financial metrics that are subject to measurement uncertainties resulting from limitations inherent in the nature and the methods used for determining such data.
The Aladdin Climate analytics are not fixed and are likely to change and evolve over time. The Aladdin Climate analytics rely on comparatively new analysis and there is limited peer review or comparable data available. BlackRock does not guarantee and shall not be responsible for the content, accuracy, timeliness, non-infringement, or completeness of Aladdin Climate analytics contained herein or have any liability resulting from the use of the Aladdin Climate analytics in this report or any actions taken in reliance on any information herein.

2050 over which such yet unpriced climate risk is getting priced in, we are also interested in the implications of climate risk for expected returns beyond 2050 when a given climate scenario will have been realized and markets fully price the cash flow implications of physical and transition risk for any single asset. This question is not only relevant against the very long-term investment horizon of an institutional investor such as KENFO, but also of relevance inasmuch as the implications of climate risk to cash flows at the asset level in the Aladdin Climate risk data need to be interpreted as *permanent* boosts or drags to cash flows, which persist beyond 2050. For the purpose of understanding how these permanent cash flow implications of climate change will affect expected returns in a given scenario beyond 2050 once they will be fully priced by markets, we build and calibrate a general equilibrium asset pricing model that allows us to address this question. For that exercise we follow Pastor, Stambaugh, and Taylor (2021) and extend their framework for understanding the impact of ESG considerations on expected returns to model cash flow implications of climate change, which then translate into expected return implications in general equilibrium.

As long as there is uncertainty over which climate scenario will be realized, i.e. over the time horizon from 2023 to 2050, we find that expected returns on asset classes consisting of equities will be affected more heavily than expected returns on fixed income asset classes as the holders of fixed income instruments are generally shielded from cash flow risk which does not lead to default. Comparing the three different scenarios we consider, we find both up to 2050 and beyond 2050 the highest impact of climate risk on expected asset class returns in the delayed transition scenario, where policies to reach net zero by 2050 are implemented too late and in a disorderly manner. By contrast, a "current policies" scenario, is associated with the smallest implications for expected returns. An orderly "net-zero 2050" scenario lies between the other two in terms of the strength of the implications on expected asset class returns. The reason for this is that physical risks are very similar across all three scenarios as the impact of policy changes on physical risks has a lag of many decades so that transition risks are the major determinant for differences in the implications of various climate scenarios for expected returns at the asset class or portfolio level. These transition risks are, by definition, lowest in a "current policies" scenario and highest in disorderly, delayed transition scenarios. However, as the Aladdin Climate data only looks ahead until 2050, we acknowledge that we might underestimate serious physical risks which are likely to occur with a lag of several decades and might make the "current policies" scenario significantly worse beyond 2050.

Applying our asset class level results to KENFO's strategic asset allocation across these asset classes, we calculate that, depending on the climate scenario, climate risk will imply a drag between 10 and 22 basis points on KENFO's expected annual portfolio return until 2050 and a somewhat higher drag between 11 and 27 basis points from 2050 onwards. We should emphasize that these estimates need to be taken with a grain of salt and not necessarily accepted at face value inasmuch as they are very much dependent on the underlying asset-level projections of cash flows up to 2050 in any given climate scenario, which are obviously subject to significant uncertainty. However, as such issues related to data quality and the accuracy of climate projections and cash flow forecasts applies in the same way if we compare KENFO's strategic asset allocation to a simple market-capitalization-weighted investment into KENFO's investible universe – which we refer to as "KENFO's investible market portfolio" – we are much more confident in drawing conclusions about climate risk in KENFO's actual strategic asset allocation *relative* to the investible market portfolio. As we calculate the corresponding annual drags on the expected return for the investible market portfolio between 2023 and 2050 to be somewhat higher in all climate scenarios, we conclude that KENFO's strategic asset allocation is already tilted towards asset classes which are expected to fare better over the coming decades in the sense of being less prone to climate risk.

The paper is organized as follows. In section 2, we describe the Aladdin Climate risk data, which we use for assessing the implications of climate risk for expected returns, and we explain how we aggregate these data to the asset class level. In section 3, we build a general equilibrium asset pricing model which integrates climate risk to cash flows. We use this framework to translate the cash flow implications of climate risk into implications for expected returns both in the case where climate scenarios are yet to be priced and when they will have been priced in. In section 4, we describe how we calibrate our model with additional non-climate-related financial data. Section 5 presents and discusses our results for expected returns at the asset class level and for KENFO's portfolio as a whole. Concluding remarks can be found in section 6.

2 Climate risk data

2.1 Blackrock's Aladdin Climate methodology

As our measure of climate risk to asset class cash flows, we resort to the Aladdin Climate methodology by Blackrock. Aladdin Climate was built to quantify climate risks and opportunities in financial terms – combining climate science, policy scenarios, asset data, and financial models to arrive at climate-adjusted valuations and risk metrics. These climate-adjusted valuation ("CAV" henceforth) metrics are based on discounted cash flow analysis in a given climate scenario relative to a benchmark scenario that is assumed to be priced into current valuations (see details on scenario below). The CAV measure accounts for two types of risks: The first source of risk is transition risk capturing the costs associated with complying with climate-related regulation on the one hand and potential revenue gains from the introduction of new climate-friendly technologies on the other hand. The second source are physical risks in the sense of the financial implications of extreme weather events caused by climate change. The impacts of transition and physical risks on the cash flows at the asset level are projected annually up to 2050 and discounted back to present value, which yields the CAV as a valuation metric. The CAV of an asset indicates by how much current valuations for the respective asset would need to be adjusted over the time horizon until 2050 if the respective climate scenario materialized until 2050. As we are interested in the implications of climate change on returns rather than valuations, we annualize the required CAV valuation adjustment from 2023 to 2050 for every single asset we consider to translate it into return implications under current market pricing.[3]

The Aladdin Climate risk data allows us to consider the following three scenarios by the NGFS (2022) in the quantitative exercises of our paper:

- The "optimistic" **net-zero 2050 scenario** involves stringent climate regulations and advancements in order to cap the rise in global temperatures at 1.5°C. This approach aims to achieve a state of balanced carbon dioxide emissions by approximately 2050 in accordance with the overarching temperature objective outlined in the Paris Agreement.[4]
- The **delayed transition scenario** envisions a situation where climate policies are not implemented until 2030. This lack of action stems from inadequate incentives provided by policymakers in the preceding years to facilitate a shift toward environmentally friendly practices. Consequently, more robust policies become necessary to contain global warming below the 2°C threshold and make up for the time lost. As a result, emissions temporarily surpass the carbon budget and their decline becomes more rapid after 2030. This accelerated reduction is essential to maintain a 67% probability of constraining the global temperature rise within the 2°C limit. However, due to the disorderly and delayed implementation of climate policies, this trajectory results in greater transitional risks compared to the orderly transition scenario. Moreover, physical risks are also elevated due to the delay in implementing climate policies.

[3] Both regarding physical risk and transition risk at the asset level, the Aladdin climate risk dataset makes an annual projection up to 2050 and then extrapolates the cash flow implications of climate risk beyond 2050 as a perpetual. Hence, cash flow implications of both types of risk are of a permanent nature and relevant beyond 2050, too. However, the CAV measure reflects the discounted cash flow drag/boost of climate risk taking both the path up to 2050 and the terminal value in 2050 (which reflects the perpetual) into account. Hence, when we compute the annualized version of the CAV using a 27-year-time horizon, we might be overestimating the impact of climate risk between 2023 and 2050 somewhat as the terminal value in 2050 is implicitly taken into account in that annualization, too. We still opt for that approach rather than separating the projection up to 2050 from the terminal value. The reasons is that we feel that this approach better reflects the forward-looking nature of financial markets which should be fully pricing a given cash flow trajectory once uncertainty over that trajectory fades out. As the scenarios we work with take 2050 as their reference point regarding the implementation of climate policies, we consider our approach to using the dataset which assumes that climate risk in a given scenario gets fully priced by 2050 (so that the terminal value is essentially zero in 2050 and the repricing happens somewhat faster between 2023 and 2050) as more realistic and consistent.

[4] We should disclose that KENFO is committed to supporting the Paris Alignment with its investments.

The postponed action leads to a more substantial increase in temperatures, subsequently causing a surge in the frequency and severity of extreme weather events.

- The **current policies scenario** portrays the enduring physical threat to the economy and financial system should the world persist in its current state. Despite a gradual reduction in European emissions, global emissions are projected to increase until 2080, resulting in a global temperature rise of approximately 3°C. This surpasses critical temperature limits, resulting in heightened physical risks and substantial costs stemming from the heightened frequency and intensity of natural disasters.

Anyone familiar with long-term cash flow projections will recognize that – even in the absence of climate risk – these projections are subject to a lot of uncertainty. Hence, one might question whether the climate-adjusted valuation metrics we obtain from Aladdin Climate risk are useful estimates to think about the return implications of climate change. Even if one may thus be skeptical about accepting the numbers we come up with for the return implications of climate risk at face value, we still think this kind of exercise is informative of at least two issues: First, as issues related to data quality affect both KENFO's actual strategic asset allocation and KENFO's investible market portfolio in the same way, we can likely obtain reliable conclusions from our analysis as to whether KENFO's strategic asset allocation contributes to making its portfolio more robust to climate risk or not. A similar argument of course applies to conclusions regarding how KENFO's portfolio will fare in any given climate scenario relative to another one. Second, even though the actual numbers we come up with might not be entirely reliable, for a long-term investor like KENFO, it is already of great help if Aladdin Climate risk gets the order of magnitude of cash flow implications in a given climate scenario about right at the asset level, so that as asset allocators, we can get a sense of the order of magnitude of the likely drag of climate risk on expected returns for which we have to prepare our portfolio for the coming decades.

2.2 Asset class coverage

Blackrock's Aladdin Climate dataset provides us with asset-level data on climate risk for a broad universe of liquid asset classes. Rather than using benchmark indices for liquid asset classes, we use KENFO's actual portfolio holdings within each asset class to aggregate the Aladdin climate data from asset-level data to asset-class-level data. The nine liquid asset classes from KENFO's strategic asset allocation which we consider for our quantitative exercise are: Developed Markets Large Cap Equity, Developed Markets Small Cap Equity, Emerging Markets

Equity, REITs, Developed Markets Government Bonds, Credit Investment Grade, Credit High Yield, Emerging Markets Bonds Hard Currency, and Emerging Markets Bonds Local Currency. For those liquid asset classes, we directly match KENFO's portfolio holdings as of November 30, 2023, with Blackrock's Aladdin Climate database.[5] We calculate the annualized return drag for the asset class as implied by climate change as the weighted average of the annualized return drags implied by the CAVs for any financial instrument which KENFO is invested in in the respective asset class as of November 30, 2023, where we use the weights of the individual assets in the respective asset class of KENFO's actual portfolio as of November 30, 2023.

In order to also include the four illiquid asset classes Private Equity, Real Estate, Infrastructure Equity, and Private Debt – which account for up to 30 percent of KENFO's target allocation, but for which we do not have climate risk data from the Aladdin Climate dataset – we build liquid proxies. For Private Debt and Real Estate, we simply work with KENFO's portfolio holdings of high yield corporate debt and listed real estate (REITs), respectively. For private equity and infrastructure, though, we deem it necessary to build actual proxy portfolios which resemble more broadly KENFO's sector tilt within those asset classes, which neither closely resemble KENFO's liquid small cap or liquid infrastructure portfolio, nor are accurately reflected by liquid benchmark indices such as global small cap indices or global listed infrastructure indices. For instance, KENFO's allocation within the infrastructure space is much more tilted towards renewable energy than what is reflected in any listed infrastructure benchmark.

To build adequate liquid proxy portfolios for the two asset classes Private Equity and Infrastructure Equity, we proceed as follows: We first identify KENFO's portfolio holdings within the two asset class Private Equity and Infrastructure Equity in terms of geographical location (country) of each investment and in terms of GICS Sub-Industries.[6] For each investment in our actual portfolio, we then screen the MSCI ACWI Index of listed equities for equities with a matching country identifier and GICS sub-industry. We then replace any investment in KENFO's portfolio with the respective matching liquid asset(s). If we find several such matching assets for a given portfolio investment, we consider them all and weight them by their relative market capitalization. For both private equity and infrastructure, we are able to match more than 60% in terms of portfolio weight with liquid equities in the same country and GICS sub-industry. For the remaining portfolio investments for which we are unable to find

[5] The Aladdin Climate data we use for our quantitative exercise is from November 2023, so that we choose November 30, 2023, as the point in time for connecting any other types of financial data we use in our quantitative exercise (cf. section 4).

[6] The GICS sub-industries in KENFO's infrastructure portfolio as of November 2023 include Alternative Carriers, Cargo Ground Transportation, Diversified Support Services, Education Services, Electric Utilities, Electronic Equipment & Instruments, Environmental & Facilities Services, Gas Utilities, Health Care Facilities, Health Care Services, Highways & Railtracks, Integrated Telecommunication Services Internet Services & Infrastructure, Managed Health Care, Marine Transportation, Multi-Utilities, Oil & Gas Drilling, Oil & Gas Exploration & Production, Oil & Gas Storage & Transportation, Other Specialized REITs, Renewable Electricity, Research & Consulting Services, Water Utilities, Wireless Telecommunication Services. Renewable Electricity accounted for around 30% of the infrastructure portfolio as of November 2023. The sub-industry mix in private equity is much broader, of course.

at least one listed equity within the same country and same GICS sub-industry, we take the market-cap-weighted universe of all listed equities around the globe with the respective GICS sub-industry. We opt for going with matching GICS sub-industries rather than matching countries in that case as there is typically wide heterogeneity across locations within a given country regarding physical risks – e.g. whether a company has its plants located mostly close to coast lines or far from them – whereas the GICS sub-industry gives quite detailed information on a company's or asset's general exposure to physical risk and also provides a more accurate measure of transition risk, which we view as being more closely tied to a business model and hence GICS sub-industry rather than a country. Notice that this procedure where we consider KENFO's particular regional and sectoral allocation within private markets implies that we obtain quite different numbers when comparing some illiquid asset classes to liquid counterparts. For instance, as our private equity allocation is tilted much more towards software companies than the global small cap index in the liquid space, the CAVs we compute at the asset-class level for private equity are much smaller in absolute value than for developed markets small cap equity.

For the different climate scenarios for which CAV is available from Aladdin Climate, we thus obtain the estimates for return implications of climate risk at the asset class level which are displayed in Table 1.

Asset Class	CAV for "net-zero 2050" scenario in % p.a.	CAV for "delayed transition" scenario in % p.a.	CAV for "current policies" scenario in % p.a.
Developed Markets Large Cap Equity	-0.28	-0.39	-0.15
Developed Markets Small Cap Equity	-0.35	-0.46	-0.17
Emerging Markets Equity	-0.34	-0.36	-0.14
REITs	-0.17	-0.15	-0.16
Developed Markets Government Bonds	-0.02	-0.01	-0.01
Credit Investment Grade	-0.05	-0.05	-0.01
Credit High Yield	-0.07	-0.09	-0.03
Emerging Markets Bonds Hard Currency	-0.12	-0.04	-0.02
Emerging Markets Bonds Local Currency	-0.10	-0.02	-0.01
Private Equity	-0.12	-0.35	-0.16

Real Estate	-0.17	-0.15	-0.16
Infrastructure Equity	-0.04	-0.30	-0.16
Private Debt	-0.07	-0.09	-0.03

Table 1: Annualized CAVs for different asset classes depending on climate scenario

Two aspects are worth highlighting about the values displayed in Table 1. First, fixed income generally receives lower numbers in absolute value. This reflects the logic that owners of an enterprise's bonds have a smaller exposure to the risks and benefits associated with climate change than owners of the stocks of the enterprise. Second, for most asset classes, the current policies scenario has the most benign effects on the annualized CAV, whereas the delayed transition scenario tends to imply the biggest drag on the required climate adjustment to valuations, which the CAV represents. This might seem counterintuitive as the delayed transition scenario represents a net zero scenario by 2050, while the current policies scenario is associated with elevated physical risk. To understand why the "current policies" scenario looks less harmful in terms of the implications of climate change for the CAV, we provide a decomposition of the figures from Table 1 in terms of the underlying physical risk and transition risk in Table 2 and Table 3 – the sum of the numbers from those two tables represents the "total" CAV for the respective asset class in the respective climate scenario displayed in Table 1.

Asset Class	CAV for "net-zero 2050" scenario in % p.a. – only physical risk	CAV for "delayed transition" scenario in % p.a. – only physical risk	CAV for "current policies" scenario in % p.a. – only physical risk
Developed Markets Large Cap Equity	-0.13	-0.14	-0.15
Developed Markets Small Cap Equity	-0.14	-0.16	-0.17
Emerging Markets Equity	-0.13	-0.14	-0.14
REITs	-0.13	-0.15	-0.16
Developed Markets Government Bonds	-0.01	-0.01	-0.01
Credit Investment Grade	-0.01	-0.01	-0.01
Credit High Yield	-0.02	-0.03	-0.03
Emerging Markets Bonds Hard Currency	-0.01	-0.02	-0.02

Emerging Markets Bonds Local Currency	-0.01	-0.01	-0.01
Private Equity	-0.14	-0.15	-0.16
Real Estate	-0.13	-0.15	-0.16
Infrastructure Equity	-0.13	-0.15	-0.16
Private Debt	-0.02	-0.03	-0.03

Table 2: Annualized CAVs for different asset classes depending on climate scenario considering only physical risk

Asset Class	CAV for "net-zero 2050" scenario in % p.a. – only transition risk	CAV for "delayed transition" scenario in % p.a. – only transition risk	CAV for "current policies" scenario in % p.a. – only transition risk
Developed Markets Large Cap Equity	-0.15	-0.26	0.00
Developed Markets Small Cap Equity	-0.21	-0.30	0.00
Emerging Markets Equity	-0.21	-0.22	0.00
REITs	-0.03	0.00	0.00
Developed Markets Government Bonds	-0.01	-0.01	0.00
Credit Investment Grade	-0.04	-0.04	0.00
Credit High Yield	-0.05	-0.07	0.00
Emerging Markets Bonds Hard Currency	-0.10	-0.02	0.00
Emerging Markets Bonds Local Currency	-0.09	-0.01	0.00
Private Equity	0.01	-0.20	0.00
Real Estate	-0.03	0.00	0.00
Infrastructure Equity	0.09	-0.15	0.00
Private Debt	-0.05	-0.07	0.00

Table 3: Annualized CAVs for different asset classes depending on climate scenario considering only transition risk

Inspecting Table 2, which contains the physical risk component, one observes that the differences across all three scenarios within any given asset class are very small. As one would expect, physical risk is generally highest for any given asset class under a “current policies” scenario and lowest under the “net-zero 2050” scenario. The reason why the differences between the annualized CAVs of three scenarios amount to less than 3 basis points, though, has to do with the fact that the physical risks associated with climate change play out with a lag of several decades, while the CAVs implied by the Aladdin Climate methodology look only until 2050. With regard to the time horizon of 2050, climate policies which are put in place today have only a very limited impact on climate change and hence physical climate risk.

While the differences in physical risk are rather small across scenarios for a given asset class, the differences in transition risk across scenarios within any given asset class as displayed in Table 3 are more pronounced. The reason for this is that transition risks become effective immediately rather than with a lag of decades like physical risks. This means that the question which climate scenario has the strongest implications on the annualized CAV within any given asset class is mostly driven by the question in which scenario transition risk for the respective asset class is the most pronounced. By definition, transition risk is zero in the Aladdin Climate data for the “current policies” scenario. The delayed transition scenario is generally associated with the highest transition risk in absolute value as a disorderly and delayed, chaotic transition implies higher costs – or provides worse transition opportunities – than an orderly transition in the “net-zero 2050” scenario. Due to the major role transition risk plays for the question which scenario is best or worst in terms of CAV for any given asset class, one thus obtains the pattern observed in Table 1, whereby the “current policies” scenario has the least severe and the “delayed transition” scenario the most severe implications for the CAV of most asset classes. Two major exceptions are Infrastructure equities and Private Equity, which actually have positive entries for transition risk in the “net-zero 2050” scenario Table 3 reflecting larger transition opportunities than transition risks in KENFO’s portfolios for these asset classes which are tilted strongly towards renewable electricity and towards application and systems software, respectively.

2.3 Climate risk’s effect on expected returns over different time horizons

The data on climate risk which we display in Table 1 are based on the assumption that the underlying cash flow implications of physical and transition risks get gradually priced in into asset valuations until 2050. Hence, they can directly be used by investors to adjust their annual return expectations for asset classes up to 2050 for different climate scenarios. However, if one seeks to look beyond 2050, one needs a different approach for adjusting expected returns for climate risk. This has to do with two aspects: On the one hand, both types of climate risk accounted for by Blackrock's Aladdin Climate risk constitute *permanent* cash flow implications at the asset level. Hence, the drag (or boost) to cash flows from physical risk and transition risks/opportunities will not vanish as soon as we will arrive in the year 2050 and find ourselves in any of the three scenarios we consider. The same drag to cash flows will persist. However, in contrast to the year 2023, those cash flow drags (or boosts) from physical and transition risks will have been priced in by markets by 2050; this follows necessarily from the logic of the "CAV" concept which implies a valuation adjustment which will materialize by 2050.

To see the difference between climate risk from the perspective of 2023 and 2050, consider a simple static model of asset returns, where any asset j delivers a cash flow d_j, which – if we consider climate risk in a given scenario k, becomes $d_j + c_{j,k}$, where $c_{j,k}$ is a negative number if physical and transition risks outweigh revenue opportunities from climate change and a positive number otherwise. The market valuation of asset j, i.e. the price investors pay for asset j, is denoted p_j. Hence, the static return an investor holding asset j earns in climate scenario k is given by $r_{j,k} = \frac{d_j + c_{j,k}}{p_j}$. Blackrock's Aladdin Climate data is constructed such that the annualized CAV informs us about the ratio $\frac{c_{j,k}}{p_j}$, i.e. about the effect of climate risk to cash flows on returns if we assume current market pricing p_j, i.e. with p_j being determined from markets actually pricing d_j rather than $d_j + c_{j,k}$ – this is the simple implication of the assumption that climate risk behind the CAV-methodology is not yet priced in by markets as of 2023. Therefore, for thinking about the implications of climate risk on annual expected returns up to 2050, an investor may simply use the annualized CAV numbers from Table 1 to adjust his return estimates for climate risk in a given scenario.

By 2050, however, markets will be pricing $d_j + c_{j,k}$ rather than d_j for the climate scenario k in which the world wakes up in 2050. But that means that asset prices p_j will change *ceteris paribus*. Hence, an investor who is interested in the question how expected returns for asset classes will be affected by climate risk from 2050 onwards, cannot use the date from Table 1, but needs to figure out how pricing by asset markets will actually change until 2050 as a result of the pricing in of climate risk in a given scenario. That information is *not* provided by the CAV. The (non-annualized) CAV only tells us for any given scenario by how much valuations are off as of *today*, i.e. in 2023, as a result of climate risk to cash flows until 2050 which is not fully priced, yet, as different scenarios and hence uncertainty about climate risk is still on the table from the perspective of 2023 – the CAV does not tell us how assets will actually be priced in 2050 once a given climate scenario is realized.

The data provided by Blackrock Aladdin Climate are still useful for addressing that question, too, as we shall argue in section 3 of this paper. The reason is that – following the logic of the simple static model – combining the CAV with data on market pricing of assets – i.e. data on p_j in today's asset markets – allows us figuring out d_j and $c_{j,k}$. Using the fact that the physical and transition risks identified by Aladdin Climate are *permanent* in nature and assuming that the materialization and "pricing in" of climate risk is the only thing which changes until 2050, we may then use a general equilibrium asset pricing model to figure out how asset markets will price climate risk from 2050 onwards when a given climate scenario k will have been realized and will be fully reflected in asset prices.

3 General equilibrium model of climate risk to asset-level cash flows

3.1 Description of the model

The formal setup which we use to model the general equilibrium asset pricing implications of climate risk to asset-level cash flows follows the work by Pastor, Stambaugh, and Taylor (2021). The major difference from their setting is that we do not directly model stochastic returns for assets. Instead, we dig one layer deeper and model stochastic cash flows at the asset level. This allows us to derive pricing implications for those cash flows as the return of an asset is jointly determined by the cash flow it generates and the price investors pay for the asset and its cash flow.

Except for the modeling of climate risk to cash flows, we consider a fairly standard one-period asset pricing model. There is a continuum of agents $i \in [0,1]$. Agent i's wealth at the beginning of the period is denoted by W_i^0. We assume that agent i's preferences over end-of-period wealth W_i^1 are given by the exponential utility function

Equation 1

$$U\left(W_i^1\right) = -e^{-A_i W_i^1} \quad \forall i \in [0,1]$$

where A_i is agent i's coefficient of absolute risk aversion. Agents allocate their wealth across N risky assets and one risk-free asset. We will generally think of these assets as representing "asset classes" in the sense of the climate risk data aggregated to the asset class level which we have presented in section 2.

For simplicity, we assume that only risky assets are subject to climate risk. There is strictly positive net supply of all risky assets $j \in \{1, \ldots, N\}$, while the risk-free asset is assumed to be in zero net supply. $x_{i,j}$ is used to denote the share of asset j in agent i's portfolio and x_i is the $N \times 1$ vector containing whose jth element is $x_{i,j}$. Any risky asset j delivers a stochastic cash flow f_j which is given by:

Equation 2

$$f_j = d_j + c_j + \varepsilon_j \quad \forall j \in \{1, \ldots, N\}$$

ε_j is the jth element of the vector ε. We assume that $\varepsilon \sim N(0, \Sigma)$, which makes the cash flows of any single asset stochastic with an $N \times N$ covariance matrix Σ, where $\sigma_{k,l}$ is supposed to be the entry in row k and column l of the covariance matrix Σ, i.e. the covariance between the cash flows of assets k and l. d_j and c_j represent asset-specific determinants of the cash flows of a given asset j. Let d and c denote the $N \times 1$ vectors whose jth elements are d_j and c_j, respectively. In the spirit of the simple "toy model" discussed in section 2.3, we work with two asset-specific determinants of cash flows to be able to independently model cash flow implications of climate risk throughout the paper. Thus, c_j ("climate risk") is supposed to capture the cash flow implications of climate change for asset j, while d_j ("dividend") represents all other "traditional" determinants of asset j's cash flows which are independent from climate risk. If $c_j > 0$, asset j benefits from climate risk in the sense that transition opportunities for the asset outweigh physical risks associated with climate change. If, by contrast, $c_j < 0$, asset j's cash flows are adversely affected by climate change, i.e. the associated physical and transition risks weigh negatively on the cash flow of the asset.

Agents are price takers in asset markets, and they also take cash flows at the asset level as given. Let r denote the $N \times 1$ vector of asset returns, whose jth element is r_j. We use r^f for the risk-free rate. Agent i's end-of-period wealth W_i^1 depends on the share in any given asset $j \in \{1, \ldots, N\}$ which is held by agent i over the single period. Let p_j denote the market capitalization of asset j at the beginning of the single period, i.e. the price of all shares in asset j, and define p to denote the $N \times 1$ vector of asset prices whose jth element is p_j. Defining the return of asset j as

Equation 3

$$r_j = \frac{f_j}{p_j} = \frac{d_j + c_j + \varepsilon_j}{p_j} - 1 \quad \forall j \in \{1, \ldots, N\}$$

W_i^1 can be expressed as follows:

Equation 4

$$W_i^1 = W_i^0 \;\; 1 + r^f + x_i{}'\left(r - r^f\right) \qquad \forall i \in [0,1]$$

The expected return of any given asset j, $\mu_j \equiv E\left(r_j\right)$, is given by:

Equation 5

$$\mu_j = \frac{d_j + c_j}{p_j} - 1 \quad \forall j \in \{1, \ldots, N\}$$

Furthermore, we generally require $\sum_{j=1}^{N} x_{i,j} = 1 \; \forall i$. As agents will be assumed to be identical for the purpose of deriving market equilibrium, this restriction basically imposes on agents' optimization problems the assumptions that the safe asset is in non-zero net supply and that leverage is not available at the aggregate level.

3.2 Solving the model

As shown in the appendix, maximizing expected utility implies that the optimal portfolio weights which agents choose in equilibrium are implicitly defined by the following system of equilibrium conditions where λ_i is the Lagrange multiplier on the constraint $\sum_{j=1}^{N} x_{i,j} = 1$:

Equation 6

$$\left(\frac{d_j + c_j}{p_j} - 1 - r^f\right) + \frac{\lambda_i}{A_i W_i^0} = A_i W_i^0 \sum_{k=1}^{N} \sigma_{j,k} x_{i,k} \quad \forall j \in \{1, \dots, N\} \quad \forall i \in [0,1]$$

Equation 7

$$\sum_{j=1}^{N} x_{i,j} = 1 \quad \forall i \in [0,1]$$

To derive market equilibrium, we follow Pastor, Stambaugh, and Taylor (2021) in imposing some simplifying assumptions regarding the heterogeneity of agents. Thus, we assume that all agents have the same relative risk aversion by imposing $A_i W_i^0 = a \; \forall i \in [0,1]$. Further, let $w_i \equiv W_i^0 / W^0$ denote agent i's share in total wealth at the beginning of the period W^0 defined as $W^0 = \int_i W_i^0 di$. The weight of any given asset j in the market portfolio, which we denote by x_j^m, is given by:

Equation 8

$$x_j^m = \int_i w_i x_{i,j} di \quad \forall j \in \{1, \dots, N\}$$

Notice that $x_j^m W^0 = p_j \; \forall j \in \{1, \dots, N\}$ has to be true. As all agents make identical portfolio choices, $\lambda_i = \lambda \; \forall i$ holds. It follows that given the vectors d and c, agents' relative risk aversion a, and the covariance matrix Σ, equilibrium market weights of the various asset classes, x_j^m, are implicitly defined by the following system of equations:

Equation 9

$$\frac{d_j + c_j}{W^0} = x_j^m \left(1 + r^f + a \left(\sum_{k=1}^{N} \sigma_{j,k} x_k^m\right) - \frac{\lambda}{a}\right) \quad \forall j \in \{1, \dots, N\}$$

Equation 10

$$\sum_{j=1}^{N} x_j^m = 1$$

Once the solution for the set of weights in the market portfolio has been determined, the set of equilibrium asset prices can be recovered by using that $p_j = x_j^m W^0\ \forall j \in \{1, \ldots, N\}$. Along with the vectors d and c, this immediately implies the equilibrium expected returns of any given asset j, which we denote by μ_j^m, since $\mu_j^m = \frac{d_j + c_j}{p_j} - 1\ \forall j \in \{1, \ldots, N\}$ (cf. Equation 5).

3.3 The initial market equilibrium: equilibrium asset prices and expected rates of return

Throughout our analysis, we choose the normalization $W^0 = 1$. This just represents a choice of units meaning that all monetary units are measured relative to the total market capitalization of all asset classes ("assets") we consider. In addition, it means that $x_j^m = p_j\ \forall j \in \{1, \ldots, N\}$, so that asset prices are directly known once we know the shares of all asset classes in the "market portfolio". We define an "initial equilibrium" representing current market pricing – i.e. the situation in 2023 where different climate scenarios are on the table and markets are thus not fully pricing climate risk for any given scenario as assumed behind Aladdin Climate's CAV – as the starting point of our analysis for thinking about the return implications of climate risk. As we can actually observe the market capitalization of all asset classes in the initial equilibrium representing market pricing as of 2023, we will use market capitalization data for calibrating the vectors x^m and p in the initial equilibrium (cf. Table 5 in section 4.4).

Since we propose to calibrate the initial equilibrium with data on the weights of the various asset classes in the market portfolio, the constraint $\sum_{j=1}^{N} x_{i,j} = 1\ \forall i$ on agents' optimization problem will naturally be satisfied in the initial equilibrium. Hence, it will generally not be binding and can be ignored for the purpose of deriving equilibrium expected returns in the initial market equilibrium representing 2023. The constraint $\sum_{j=1}^{N} x_{i,j} = 1\ \forall i$ does matter, however, for the long-run equilibrium in which markets reprice climate risk as we discuss below (cf. section 3.5). As the initial market equilibrium characterized by a given set of asset class weights x^m represents an unconstrained optimum of the model laid out and solved in the preceding sections, the asset class weights x^m solve the system of equilibrium conditions

Equation 11

$$\frac{d_j + c_j}{W^0} = x_j^m \left(1 + r^f + a \sum_{k=1}^{N} \sigma_{j,k} x_k^m\right) \qquad \forall j \in \{1, \ldots, N\}$$

This is equivalent to the system presented in Equation 9 and Equation 10 for an unconstrained optimum, i.e. without the constraint in Equation 10. Under our normalization $W^0 = 1$ implying $x_j^m = p_j\ \forall j \in \{1, \ldots, N\}$ and using the definitions of expected returns from Equation 5 and the covariance matrix Σ, we can re-write Equation 11 as follows:

Equation 12

$$\mu^m = a\Sigma x^m + r^f$$

Equation 12 is very useful for our purposes as it implies that – similarly to the asset allocation approach due to Black and Litterman (1992) – we can easily recover the vector μ^m, which states expected returns in the initial market equilibrium representing the state of asset markets in 2023. In particular, we can derive μ^m from three pieces of information: A covariance matrix Σ for the asset classes we consider, the vector of market portfolio weights x^m for those asset classes, and a value for the relative risk aversion parameter a. We explain in detail in section 4 how we suggest calibrating these three pieces to obtain expected returns in the initial market equilibrium.

Once we have obtained the vector of commonly expected returns μ^m in the initial market equilibrium following a kind of “Black-Litterman procedure” as just described, we can also recover the “traditional” cash flow vector d which markets are pricing if we make an assumption how markets are pricing climate risk to the cash flow of any given asset class, i.e. if we make an assumption about the vector c as perceived by the market as of 2023. To see this, notice that the expected rate of return of any asset class j, μ_j, is given by the ratio of the cash flow of asset class j which markets are anticipating over the price of asset j, p_j (cf. Equation 5). We know the vector of equilibrium asset prices p based on our normalization of W^0 implying $x_j^m = p_j \; \forall j \in \{1, \dots, N\}$ along with information on the vector of asset class weights in the market portfolio (cf. Table 5 in section 4.4). Thus, we can easily compute the cash flow markets are pricing for any asset class j as the product of p_j and the market’s expectation of the return of asset class j, μ_j^m. We can thus obtain $d_j + c_j$ from that product of p_j and μ_j^m.

The Blackrock Aladdin Climate data we use in the quantitative section of the paper does not tell us separately about the c_j which markets are pricing and the c_j which is actually relevant in a given climate scenario, but only about the “delta” between the climate risk to asset-level cash flows which markets are pricing and which they are not pricing (yet) *conditional on* a given climate scenario (cf. the discussion in section 2.3). Hence, throughout our work, we make the analytically convenient assumption that markets are pricing $c_j = 0 \; \forall j \in [1, \dots, N]$ in the initial equilibrium. This is *not* to say that we mean to suggest that markets are not pricing any climate risk as of today – that convenient assumption just reflects the fact that all that is relevant for our exercise in this paper is *unpriced* climate risk in the logic of Aladdin Climate’s CAV, whereas the absolute level of how much of currently priced cash flows is already “climate aware”, i.e. related to c_j as opposed to d_j, is not of any relevance *per se*.

3.4 Implications of unpriced climate risk on expected returns from 2023 to 2050 ("long run")

The Blackrock Aladdin Climate dataset is based on the assumption that there is currently unpriced climate risk to cash flows up to 2050 for any given climate scenario. Thus, for the purpose of adjusting expected asset class returns in a given climate scenario for climate risk, one can take the vector of asset prices from the initial equilibrium defined in section 3.3 as given. The definition of expected returns in Equation 5 along with the analytically convenient assumption of $c_j = 0\, \forall j \in [1, \dots, N]$ in the initial equilibrium then implies that the difference between a "climate-aware" and a "non-climate-aware" expected rate of return for asset class j under a given climate scenario up to 2050, which we denote by $\Delta_j^{2023-2050}$, is simply given by:

Equation 13

$$\Delta_j^{2023-2050} = \frac{c_j}{p_j^m} \quad \forall j \in [1, \dots, N]$$

Thus, one simply needs to add the term $\Delta_j^{2023-2050} = \frac{c_j}{p_j^m}$ from the perspective of a long-term investor who seeks to be aware of unpriced climate risk to go from a non-climate-aware return expectation for any given asset class $j \in [1, \dots, N]$ to an expected rate of return which accounts for markets' misperception of climate risk for the time horizon up to 2050 under a given climate scenario. This is very convenient as the Aladdin Climate data provide us with information that speaks directly to $\frac{c_j}{p_j^m}$ for any given scenario once it is annualized (cf. section 2.3). Hence, Table 1 already contains our results for $\Delta_j^{2023-2050}\, \forall j \in [1, \dots, N]$.

Notice that by means of multiplying those data for $\frac{c_j}{p_j^m}$ by p_j^m, which, under our normalization $W^0 = 1$, we essentially know from the vector of market shares x_j^m, we can recover the vector of cash flow implications of climate risk, i.e. the vector c. This is important for the return implications for the horizon beyond 2050 inasmuch as we shall assume in accordance with the Aladdin Climate methodology that those cash flow implications are permanent and will not vanish with the realization (or pricing) of any given climate scenario by 2050.

3.5 Implications of fully priced climate risk on expected returns from 2050 onwards ("very long run")

To derive return implications of climate risk beyond 2050 when a given climate scenario will have been realized and will thus fully be reflected in asset prices, one needs to proceed as follows within the logic of the formal model we have developed: Using the value for non-climate-related "traditional" cash flows d and the relevant vector c

capturing the climate implications for cash flows in the relevant scenario, which we have backed out from the initial equilibrium as described in section 3.3, one obtains a new vector of equilibrium market portfolio weights $x^{m,2050}$ from the system of market equilibrium conditions formed by Equation 9 and Equation 10.[7] As in the initial equilibrium, our normalization of $W^0 = 1$ implies that asset prices correspond to weights in the "market portfolio", so it follows that $x^{m,2050} = p^{m,2050}$. Thus, one directly obtains a solution for asset prices, too, for the case of a new equilibrium in 2050, where markets price in climate risk in accordance with the climate scenario which has actually been realized by then. One can then compute the market's long-term "climate aware" return expectations for asset class j from the perspective of 2050 as $\mu_j^{m,2050+} = \frac{d_j + c_j}{p_j^{m,2050}} - 1$ (cf. Equation 5) using the new long-run equilibrium asset price vector $p^{m,2050}$, the non-climate-sensitive cash-flow vector d as backed out from the initial equilibrium of 2023 (cf. section 3.3), and the vector c which markets end up pricing by 2050 in the climate scenario which ends up actually being realized by then. Hence, the return differential required to account for the effect of climate risk on expected returns in a given climate scenario from 2050 onwards is given by:

Equation 14

$$\Delta_j^{2050+} = \mu_j^{m,2050+} - \mu_j^m = \frac{d_j + c_j}{p_j^{m,2050}} - \frac{d_j}{p_j^m} \quad \forall j \in [1, \dots, N]$$

4 Model calibration for deriving expected return implications beyond 2050

For the purpose of deriving the long-run return differentials Δ_j^{2050+} indicating the effects of climate risk on expected returns beyond 2050, we need to calibrate the covariance matrix Σ, the risk aversion parameter a, the risk-free rate r^f, and the vector of market capitalization weights of our asset classes in the initial equilibrium of 2023, x^m. We now describe how we do this.

4.1 Covariance matrix of asset classes

To calibrate the covariance matrix Σ from our theoretical framework, we proceed as follows: The covariance matrix we use is computed directly from time series for asset class benchmarks. For the liquid asset classes, we use the asset class benchmarks which actually underlie KENFO's strategic asset allocation. For the four illiquid asset classes we use liquid proxies which reflect KENFO's geographical allocation targets for each of these asset

[7] While we do not have to impose the constraint $\sum_{j=1}^{N} x_{i,j} = 1 \; \forall i$ (Equation 10) for deriving the initial equilibrium due to the fact that we propose to calibrate the model with a vector of weights in the market portfolio x^m which adds up to one, we now need that constraint solving the model for x^{lr} for given vectors c and d.

classes and which we adjust – where appropriate – for leverage in order to accurately reflect the true risk properties and hence "true" volatility of these asset classes: We thus use a levered small cap index for private equity, an unlevered REITs index for real estate, a blend of listed infrastructure indices for infrastructure equity, and a levered high yield index for private debt. Using time series data from January 2003 for these benchmarks up to and including November 2023, we thus work with the covariance matrix implied by Table 4 which, to simplify interpretation, we display in terms correlations and volatilities of the asset classes. Notice that all return time series and market capitalization data as well as implied expected returns which we use throughout this paper are in Euros.

Asset Class	Developed Markets Large Cap Equity	Developed Markets Small Cap Equity	Emerging Markets Equity	REITs	Developed Markets Government Bonds	Credit Investment Grade	Credit High Yield	Emerging Markets Bonds Hard Currency	Emerging Markets Bonds Local Currency	Private Equity	Real Estate	Infrastructure Equity	Private Debt	Volatility in % p.a.
Developed Markets Large Cap Equity	1.00													13.0
Developed Markets Small Cap Equity	0.94	1.00												17.2
Emerging Markets Equity	0.76	0.75	1.00											17.4
REITs	0.78	0.79	0.60	1.00										17.7
Developed Markets Government Bonds	-0.03	-0.07	-0.03	0.18	1.00									3.8

Credit Investment Grade	0.39	0.40	0.41	0.51	0.67	1.00								5.0
Credit High Yield	0.65	0.70	0.65	0.65	0.12	0.71	1.00							8.3
Emerging Markets Bonds Hard Currency	0.47	0.49	0.56	0.56	0.42	0.84	0.82	1.00						8.8
Emerging Markets Bonds Local Currency	0.54	0.47	0.65	0.54	0.25	0.47	0.49	0.57	1.00					8.8
Private Equity	0.94	0.98	0.75	0.78	-0.07	0.38	0.66	0.45	0.50	1.00				20.3
Real Estate	0.78	0.79	0.60	0.98	0.19	0.54	0.67	0.59	0.50	0.76	1.00			13.7
Infra-structure Equity	0.79	0.72	0.62	0.76	0.19	0.48	0.57	0.50	0.60	0.72	0.75	1.00		12.0
Private Debt	0.62	0.66	0.62	0.59	0.11	0.67	0.90	0.74	0.44	0.61	0.62	0.50	1.00	11.7

Table 4: Assumptions regarding correlation and volatility for constructing the covariance matrix

4.2 Asset class weights

To calibrate the vector of asset class weights in the market portfolio, x^m, we use data on the market capitalization of the same liquid asset class benchmarks which we have used for the covariance matrix per November 30, 2023, and Preqin data on the assets under management and dry powder in our four illiquid asset classes net of secondaries and fund of funds per March, 2023, which was the latest available data point. As we generally use KENFO's strategic asset class benchmarks which typically reflect particular geographical weightings across regions as well as sector- or credit-rating-based exclusions, liquidity requirements, etc., we interpret the market portfolio as the market portfolio which is actually investible for KENFO rather than as the actual market portfolio comprising all assets in global financial markets. Based on these market capitalization data, we compute asset class weights in KENFO's investible market portfolio by means of dividing the market capitalization of each asset class by the sum of market capitalizations of all asset classes we consider. This results in the asset class weights displayed in Table 5. For instance, the fact that real estate accounts for only 2% of the global market capitalization according to these data mirrors the fact that we use fund raising by closed-end real estate investment funds to represent the market capitalization of the asset class. This captures the relevant part of the asset class for KENFO's purposes, but is of course only a part of the much broader asset class "real estate" which might be relevant to other investors.

Asset Class	Weight in the Market Portfolio
Developed Markets Large Cap Equity	29.25%
Developed Markets Small Cap Equity	3.99%
Emerging Markets Equity	24.00%
REITs	0.79%
Developed Markets Government Bonds	18.67%
Credit Investment Grade	3.98%
Credit High Yield	1.59%
Emerging Markets Bonds Hard Currency	0.42%
Emerging Markets Bonds Local Currency	1.68%
Private Equity	10.21%
Real Estate	1.97%
Infrastructure Equity	1.49%
Private Debt	1.96%

Table 5: Asset class weights according to market capitalization as of November 30, 2023

4.3 Calibration of risk aversion parameter and risk-free rate

We set the risk-free rate r^f equal to 3.40%, which corresponds to the yield of German government bonds with a maturity of one year per November 30, 2023. Using Equation 12, we then pick the risk aversion parameter a such that given the covariance matrix Σ and the vector of market portfolio weights x^m as implied by the data in Table 4 and Table 5 as well as $r^f = 3.40\%$, the difference in expected returns on Developed Markets Government Bonds and Credit Investment Grade corresponds to 98 basis points, which is what we observe as yield differential between KENFO's respective two asset class benchmarks as of November 30, 2023. In Table 6, we display the resulting equilibrium expected returns μ^m as implied by Equation 12 for our choice of a and r^f. These returns happen to be broadly in line with KENFO's actual return expectations for those asset classes of November 30, 2023.[8]

Asset Class	Expected Return in % p.a.
Developed Markets Large Cap Equity	8.54
Developed Markets Small Cap Equity	10.09
Emerging Markets Equity	9.95
REITs	9.26
Developed Markets Government Bonds	3.49
Credit Investment Grade	4.47
Credit High Yield	5.94
Emerging Markets Bonds Hard Currency	5.60
Emerging Markets Bonds Local Currency	5.75
Private Equity	11.31
Real Estate	7.90
Infrastructure Equity	7.31
Private Debt	6.81

Table 6: Expected market returns μ^m in the calibrated initial market equilibrium as of November 30, 2023

5 Results

5.1 Results for 2023-2050

Against the backdrop of the general equilibrium model presented in section 3, for the time horizon from 2023 to 2050, the return deltas $\Delta_j^{2023-2050}$ for all asset classes in KENFO's portfolio are simply given by the annualized CAVs as displayed in Table 1 (cf. section 3.4). These are obtained by means of aggregating and annualizing the CAV data which Aladdin Climate features for the asset level as described in section 2.

Using the results displayed in Table 1 along with the weights of the various asset classes in KENFO's strategic asset allocation as of November 2023, we expect an annual return drag to KENFO's portfolio between 2023 and 2050 due to climate change which amounts to…

- … 10 basis points in the "current policies" scenario.
- … 15 basis points in the "net-zero 2050" scenario.

[8] Notice that the returns displayed in Table 6 are "discrete" returns from a static, one-period model. Their "compounding" counterparts would be somewhat lower. This needs to be kept in mind when comparing the numbers in Table 6 to return assumptions which are usually stated in compounding terms.

- … 22 basis points in the "delayed transition" scenario.

If we use the investible market portfolio weights from Table 5 instead of KENFO's actual allocation within that investible universe, we rather obtain the following numbers for the expected annual return drag on the "market portfolio" due to climate change between 2023 and 2050:

- 11 basis points for the "current policies" scenario.
- 20 basis points for the "net-zero 2050" scenario.
- 27 basis points for the "delayed transition" scenario.

Comparing the results for KENFO's current strategic asset allocation to those for KENFO's actually investible market portfolio, one may conclude that KENFO's current strategic asset allocation is already tilted towards asset classes which are expected to fare better in the three climate scenarios which we consider for the time horizon up to 2050. Hence, KENFO's existing strategic asset allocation is already more robust to climate risk than "the market portfolio".

5.2 Results beyond 2050

Going through the procedure outlined in section 3.5 to construct return implications from 2050 onwards when a given climate scenario will have been realized and will thus have been fully priced into asset prices, we obtain the quantitative results displayed in Table 7 for the very-long-run return deltas Δ_j^{2050+} based on the Aladdin Climate data described in section 2 and the calibration of model parameters described in section 4.

Asset Class	Return delta from 2050 onwards for "net-zero 2050" scenario in percentage points p.a.	Return delta from 2050 onwards for "delayed transition" scenario in percentage points p.a.	Return delta from 2050 onwards for "current policies" scenario in percentage points p.a.
Developed Markets Large Cap Equity	-0.20	-0.27	-0.11
Developed Markets Small Cap Equity	-0.20	-0.27	-0.11
Emerging Markets Equity	-0.20	-0.27	-0.11
REITs	-0.20	-0.27	-0.11
Developed Markets Government Bonds	-0.20	-0.26	-0.11

Credit Investment Grade	-0.20	-0.26	-0.11
Credit High Yield	-0.20	-0.27	-0.11
Emerging Markets Bonds Hard Currency	-0.20	-0.27	-0.11
Emerging Markets Bonds Local Currency	-0.20	-0.27	-0.11
Private Equity	-0.20	-0.27	-0.11
Real Estate	-0.20	-0.27	-0.11
Infrastructure Equity	-0.20	-0.27	-0.11
Private Debt	-0.19	-0.26	-0.10

Table 7: Annual return deltas from 2050 onwards by asset class depending on climate scenario realized by 2050

Disregarding rounding errors, the expected return implications of the various climate scenarios are thus virtually the same across all 13 asset classes and amount to around 20 basis points for the "net-zero 2050" scenario, about 27 basis points for the "delayed transition" scenario, and about 11 basis points for the "current policies" scenario. This ranking of scenarios reflects the observations from section 2 of the paper whereby the "current policies" scenario generally has the least pronounced implications for cash flows and valuations due to the high similarity of physical risks until 2050 and the absence of any transition risks in that scenario. As transition risks are highest in the "delayed transition" scenario and as the cash flow implications of climate risk – both regarding transition risk and physical risk – are of a permanent nature so that they apply even beyond 2050, we obtain the largest drag on expected returns for the time horizon beyond 2050 for the "delayed transition" scenario and the smallest one for the "current policies" scenario.

The reason for which one obtains virtually the same implications for expected returns across all asset classes within a given scenario is as follows: Once a given scenario has been priced, the cash flows of all asset classes change in a *deterministic* manner according to the cash flow vector c identified in section 3. Deterministic, i.e. risk-free boosts or drags to cash flows are fully arbitraged away by efficient financial markets, though. In particular, one would expect investors to substitute out of asset classes, which – without any repricing – would see a relatively larger drag to expected returns due to the implications of climate change for cash flows, and substitute into asset classes with a relatively lower drag to expected returns due to climate change in the absence of any repricing.

Figure 1, Figure 2, and Figure 3 illustrate that this substitution pattern in fact takes place between the initial equilibrium from section 3.3 characterizing the state of asset markets in 2023 and the new long-run equilibrium from section 3.5 which obtains in 2050 when a given climate scenario is fully priced. As a proxy for the drag to expected returns which would directly obtain due to climate change without any market repricing, we can use the annualized CAVs (or "long-run expected return deltas") from Table 1 relative to expected returns in the initial equilibrium as displayed in Table 6. This provides us with a measure of the relative drag to expected returns one would observe from the cash flow drag to climate change if markets were not pricing that effect, i.e. if agents would not reoptimize. This measure on the horizontal axes of Figure 1, Figure 2, and Figure 3 thus shows for any asset class how strong the incentives are to substitute away or into from this asset class due to the relative return drag.

As a measure for the substitution pattern in which agents actually engage as one moves from the initial equilibrium which portrays markets in 2023 to the new long-run equilibrium for a given scenario which obtains in 2050 and in which markets fully price the respective realized climate scenario, we use the percentage change in the investible market portfolio weight of the respective asset class between the initial equilibrium from section 3.3 and the new long-run equilibrium as characterized in section 3.5.[9]

As one can see very clearly from the almost linear relationships in Figure 1, Figure 2, and Figure 3, agents substitute into (i.e. drive up the market cap of) asset classes with a lower return drag from climate change in the initial equilibrium at the expense of the market cap of asset classes with a higher return drag from climate change in the initial equilibrium.

[9] Notice that Figure 1, Figure 2, and Figure 3 contain in fact changes between the percentage shares in the investible market portfolios of 2023 and 2050 in percentages, not percentage points. Looking at percentage point differences would not illustrate the substitution pattern in markets between the initial equilibrium as of 2023 and the new long-run equilibrium in 2050 because percentage point differences would be dominated by the different orders of magnitude of the different asset classes in the initial equilibrium as calibrated with the values from Table 5.

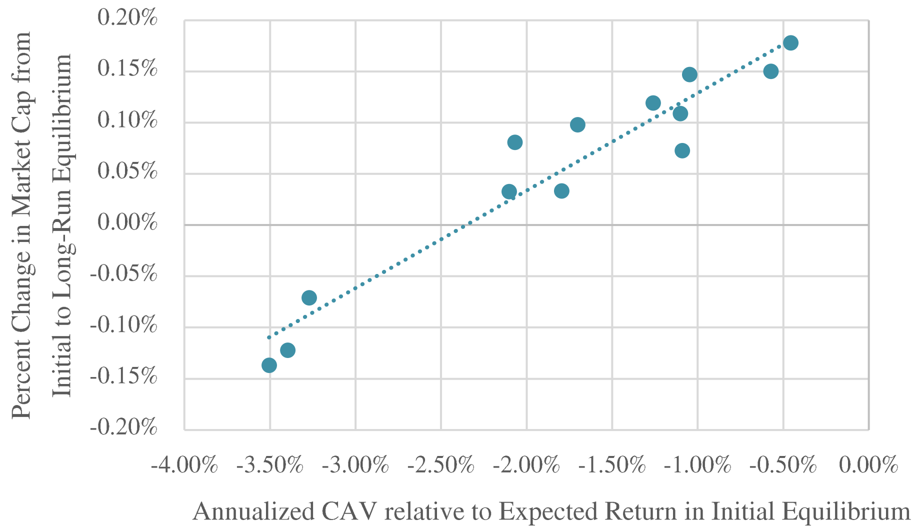

Figure 1: Drag on expected returns from climate change in initial equilibrium and substitution pattern between initial equilibrium and long-run equilibrium for "net-zero 2050" scenario

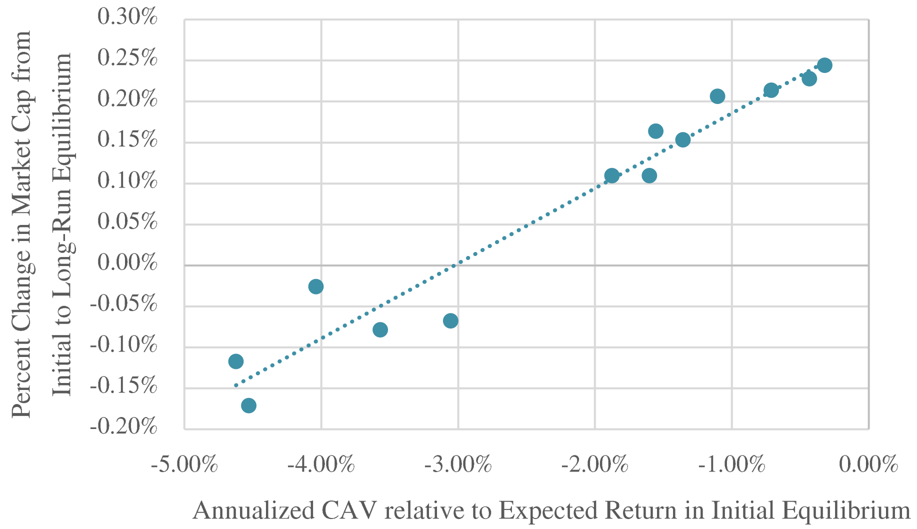

Figure 2: Drag on expected returns from climate change in initial equilibrium and substitution pattern between initial equilibrium and long-run equilibrium for "delayed transition" scenario

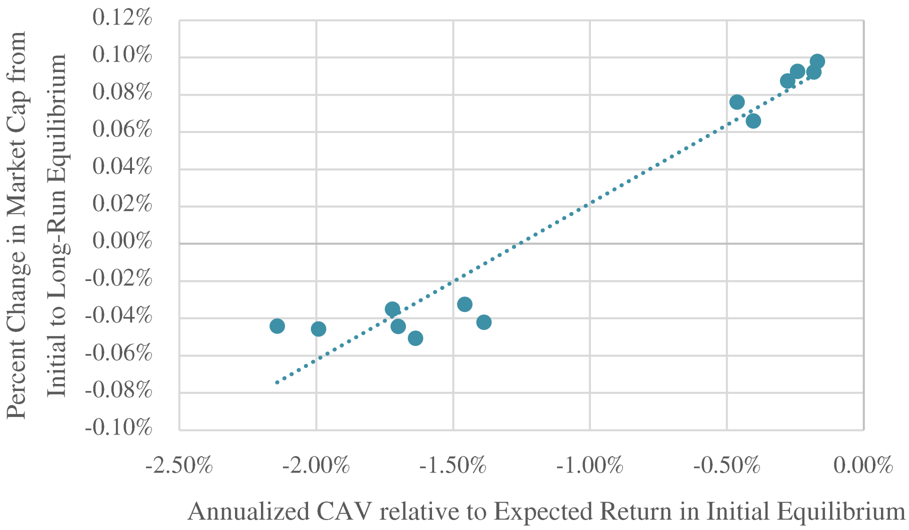

Figure 3: Drag on expected returns from climate change in initial equilibrium and substitution pattern between initial equilibrium and long-run equilibrium for "current policies" scenario

This type of substitution illustrated by Figure 1, Figure 2, and Figure 3 does imply market repricing of the cash flow drags of climate change and hence an adjustment of expected returns as one moves from the initial equilibrium of 2023 to the new long-run equilibrium in 2050, though. As the relative market capitalization goes up (down) in the general equilibrium setting laid out in section 3, expected returns for the respective asset class necessarily go down (up); for a given cash flow, a higher (lower) asset price necessarily depresses (boosts) expected returns. Due to the strong negative correlations illustrated by Figure 1, Figure 2, and Figure 3, this "repricing" effect thus works in the exact opposite direction of the "direct" drag on expected returns resulting from the cash flow drags of climate change for given market prices in the initial equilibrium. As financial theory would imply, the two effects are indeed exactly offsetting, so that markets fully arbitrage away these deterministic cash flow drags in the new long-run equilibrium so that in the end, one is left with expected return deltas in the long-run equilibrium which are identical across asset classes for a given scenario (cf. Table 1Table 7). In general, expected returns end up being lower across the board in the new long-run equilibrium as the cash flows for virtually all asset classes are assumed to be permanently lower relative to the amount of financial wealth to be allocated, W^0.[10]

Hence, based on the quantitative results reported in Table 7 which indicate that asset class returns change by similar amounts, we can conclude that looking beyond 2050, irrespective of how KENFO's strategic asset allocation may

[10] Recall from the discussion in section 3 that the vector of permanent cash flow drags can be backed out from the Aladdin Climate data in Table 1 by means of multiplying them with asset prices, which under our normalization of $W^0 = 1$ correspond to the weights in the investible market portfolio displayed in Table 5.

change in the meantime, we would expect an annual investment return from 2050 onwards which, due to climate change, is lower by around…

- … 11 basis points if the "current policies" scenario is realized by 2050.
- … 20 basis points if the "orderly transition" scenario is realized by 2050.
- … 27 basis points if the "delayed transition" scenario is realized by 2050.

These figures are somewhat higher than what we project for KENFO's portfolio as an annual drag between 2023 and 2050 (cf. section 5.1). However, they are in line with what we report in section 5.1 for KENFO's investible the market portfolio as an annual return drag between 2023 and 2050. Thus, it would not be correct to say that climate change has more severe drags on expected returns in the very long run. Instead, the drag from climate change on KENFO's expected portfolio return only becomes larger from 2050 onwards due to the fact that KENFO's current strategic asset allocation is tilted towards asset classes with a lower drag on expected returns between 2023 and 2050 when the underlying cash flow drags are not yet fully priced in, while such tilting will no longer be possible once markets fully price those cash flow drags by 2050 in the specific scenario which will be realized by then.

6 Conclusion

We have derived the implications of various climate scenarios for expected returns at the asset class level and for KENFO's strategic asset allocation until 2050 and beyond. While the exact numbers we come up with need to be taken with a grain of salt due to significant forecast uncertainty regarding cash flows up to 2050, we still think that we can draw some reliable conclusions from this kind of exercise, which are less subject to such issues with data quality. First, as such data quality issues would apply equally to KENFO's strategic asset allocation and KENFO's investible market portfolio, the analysis suggests that KENFO's strategic asset allocation does address climate risk better than a passive, market-capitalization based investment into KENFO's investment universe, aka "KENFO's investible market portfolio". Second, if one is willing to accept that the Aladdin Climate risk data at least get the order of magnitude of cash flow risk from climate change about right – which is a view we would feel comfortable with - the size of the expected return drags from climate change over the coming decades seems to be manageable against the backdrop of KENFO's return targets.

However, we acknowledge that due to data limitations with the Aladdin Climate scenarios, which look only until 2050 and which identify permanent drags to cash flows at the asset level which arise until then, we might be underestimating the very-long-run impact of climate risk on expected returns beyond 2050. The effects of policy changes on physical risks play out with a lag of decades and would thus be expected to become much more severe in the second half of the 21st century or in the 22nd century. By simply extrapolating the permanent cash flow implications in the Aladdin Climate database for the time horizon up to 2050 beyond that time horizon, we might thus be underestimating physical risks as we start looking very far beyond 2050. This would be particularly relevant for the "current policies" scenario which would result in a "hot house world" with much more severe physical risks in the long term. Hence the seemingly limited implications of a "current policies" scenario beyond 2050 as suggested by our work need to be interpreted with great caution. Revisiting these results based on asset level data which look further into the future might be a worthwhile direction for future research.

In addition, the implicit assumption that there is not any uncertainty about climate change from 2050 onwards, which underlies the Aladdin Climate data which we use in this paper, is likely inaccurate. If there is still uncertainty and hence unpriced climate risk from 2050 onwards – just with a different set of scenarios than as of today – we would of course obtain different return implications across all major asset classes in our analytical framework. This would also imply room for tilting KENFO's strategic asset allocation towards asset classes which are more robust to climate risk beyond 2050. For addressing that very-long-term issue, though, one would need asset level data which look further into the future than 2050, too. Apart from that, we have ignored the effects of any non-financial objectives in investors' objective functions such as a "taste for ESG", which can have significant effects on long-term expected returns as demonstrated theoretically by Pastor, Stambaugh, and Taylor (2021) and analyzed in the context of large institutional portfolios by NBIM (2021), for instance.

Appendix

Derivation of Optimality Condition for Optimal Portfolio Weights in Equation 6:

Using the utility function $U\left(W_i^1\right) = -e^{-A_i W_i^1}\ \forall i \in [0,1]$ along with $W_i^1 = W_i^0\left(1 + r^f + x_i{}'\left(r - r^f\right)\right)\quad \forall i \in [0,1]$ implies that expected utility is given by:

Equation 15

$$E\left\{U\left(W_i^1\right)\right\} = E\left\{-e^{-A_i W_i^0\left(1+r^f+x_i{}'\left(r-r^f\right)\right)}\right\} = -e^{-A_i W_i^0\left(1+r^f\right)} E\left[e^{-A_i W_i^0 x_i{}'\left(r-r^f\right)}\right]$$

$$= -e^{-A_i W_i^0\left(1+r^f\right)} e^{-A_i W_i^0 x_i{}' E\left(r-r^f\right)+\frac{1}{2}A_i{}^2\left(W_i^0\right)^2 x_i{}' Var\left(r-r^f\right) x_i}$$

$$= -e^{-A_i W_i^0\left(1+r^f\right)} e^{-A_i W_i^0 \sum_{j=1}^{N} x_{i,j}\left(\frac{d_j+c_j}{p_j}-1-r^f\right)+\frac{1}{2}A_i{}^2\left(W_i^0\right)^2 \sum_{j=1}^{N}\sum_{k=1}^{N}\sigma_{j,k}x_{i,j}x_{i,k}}$$

The third equality obtains using the properties of the log-normal distribution. To arrive at that fourth equality, we use that agents behave as price takers in asset markets, so that they do not internalize any potential dependence of equilibrium asset prices on moments of the return distribution, which implies that from the perspective of any agent engaging in this type of expected utility maximization, the vector ε is the only stochastic component in $E\left(r - r^f\right)$ and $Var\left(r - r^f\right)$. This also implies $E\left(r - r^f\right) = E(r) - r^f$ and $Var\left(r - r^f\right) = Var(r)$. Thus, with the help of the expression for r from Equation 3, one arrives at the fourth equality.

The first-order conditions for maximizing expected utility by means of choosing portfolio weights under the constraint $\sum_{j=1}^{N} x_{i,j} = 1\ \forall i$ are:

Equation 16

$$-A_i W_i^0\left(\frac{d_j + c_j}{p_j} - 1 - r^f\right) + \frac{1}{2}A_i{}^2\left(W_i^0\right)^2 \sum_{k=1}^{N} 2\sigma_{j,k}x_{i,k} - \lambda_i = 0\quad \forall j \in \{1, \ldots, N\}\quad \forall i$$

Equation 17

$$\sum_{j=1}^{N} x_{i,j} = 1\quad \forall i$$

λ_i is the Lagrange multipliers on the constraint $\sum_{j=1}^{N} x_{i,j} = 1\ \forall i$. Rearranging terms in Equation 16 then yields the expression in Equation 6 in the main text.

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