The Risk and Reward of Investing*

Ronald Doeswijk† Laurens Swinkels‡

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Abstract

We examine the risks and rewards of investing by constructing a comprehensive market portfolio valued at $150 trillion in global assets and spanning 1970–2022 at a monthly frequency. The monthly frequency allows for a more accurate estimation of investment risks compared with previous studies. Even though the Sharpe ratio of the global market portfolio is not much higher than that of equities, it is much more stable over time. Moreover, drawdowns of the global market portfolio are less deep and shorter. When the market portfolio is expressed in currencies other than the U.S. dollar, risks of investing appear larger. *JEL Codes: G11, G12.*

Keywords: Strategic Asset Allocation, Market Portfolio, Historical Returns, Investment Risk

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†Independent, ronalddoeswijk@yahoo.com

‡Corresponding author. Erasmus University Rotterdam, Erasmus School of Economics, Burgemeester Oudlaan 50, NL-3062 PA, Rotterdam, Netherlands, lswinkels@ese.eur.nl and Robeco Asset Management, l.swinkels@robeco.com

1 Introduction

Standard financial economics theory prescribes investing in a diversified 'market portfolio' comprising of all assets. What is the risk of this market portfolio? With an unrivalled global dataset that basically comprises all investable assets and is based on market prices at monthly frequency, we examine the global market portfolio's risk and reward characteristics over more than half a century. Until now, the risk of investing in the market portfolio has received little attention. Returns at the monthly frequency allows us to add a more precise risk dimension to the groundbreaking work of Jordà et al. (2019). The returns on the market portfolio reflect changes in aggregate invested wealth. Since financial markets and the real economy are intertwined (see Titman (2013)), the fluctuations in aggregate investor wealth are important as they may also have real economic effects. Returns on the market portfolio also provide valuable input for debates on inequality (see Piketty (2011) and Piketty and Zucman (2014)), more specifically on investment returns versus economic growth (also known as 'r minus g', see Barro (2023)).

Because of data limitations, existing research has assumed that the investable asset universe is limited to public equities or has used a broader set of assets with returns measured at the annual frequency, which masks shorter-term variation in prices. We show that the measured return characteristics of the global market portfolio change in quantitatively important ways when a comprehensive set of assets measured at a monthly frequency is used. In this paper, we report on the stability of Sharpe ratios of the market and asset classes over time. We also study the severity, frequency, and duration of drawdowns. Finally, we examine the influence of measurement currency on the risks and rewards of the global market portfolio.

This study extends prior research documenting historical international returns at the *annual* frequency. Dimson et al. (2002) construct annual returns of an equity market index with sixteen countries included, and they also calculate returns on a GDP-weighted long-dated government bond index starting in 1900. Instead, our government bond index represents a market-capitalization-weighted all-maturities index. Jordà et al. (2019) report annual returns on wealth by country and cross-sectional equally weighted and GDP-weighted period averages starting as early as 1870.[1] The seminal work of Ibbotson and Siegel (1983) —updated in Ibbotson et al. (1985)— collects annual returns on their world wealth portfolio for the period 1960–1980. Doeswijk et al.

[1]The Golez and Koudijs (2018) analysis even spans four centuries and consists of Dutch and U.K. (1629–1812), U.K. (1813–1870), and U.S. (1871–2015) stock markets.

(2020) is the only study after Ibbotson and Siegel (1983) to compile a long-term time series of annual returns for a global multiasset market portfolio. Their invested global market portfolio covers the 1960–2017 period and excludes privately held real estate, but compared to Ibbotson and Siegel (1983) adds international real estate and more recent asset classes like private equity, inflation-linked bonds, and emerging market debt. No matter how insightful these studies at the *annual* frequency are at estimating long-term average returns, the risks involved with investing can be estimated much more accurately with *monthly* returns. For example, Danielsson et al. (2018) estimate stock market risks using monthly data going back two centuries.

Our contribution to the literature is threefold: creation of a new dataset of monthly returns on the global market portfolio, analyses of the risk of investing beyond standard risk measures, and an examination of the impact of the measurement currency on the risk and reward of investing.

Regarding our first contribution we construct a novel comprehensive dataset of the global market portfolio currently worth $150 trillion in assets invested in by financial investors and spanning the period 1970–2022 at a monthly frequency. This is a markedly larger market portfolio than the $32 trillion of the S&P 500 index, which is often used as a proxy for the market portfolio in empirical studies. Our global market portfolio covers five asset categories: (i) equities broad, which consists of equities and private equity; (ii) real estate;[2] (iii) nongovernment bonds, which consist of investment-grade credits, high-yield corporate bonds, and leveraged loans; (iv) government bonds broad, which consists of government bonds, emerging markets bonds, and inflation-linked bonds, and (v) commodities broad, which consist of commodities held for investment (predominantly gold) and cryptocurrencies.[3] We have made the monthly returns series of the market portfolio publicly available, to facilitate its use, as well as for replication purposes and extensions.

Our main findings regarding the first contribution can be summarized as follows. The geometric (arithmetic) average excess return of the global market portfolio has been 0.30 (0.34) percent per month over the period 1970–2022, while the standard deviation of returns has been 2.90 percent. Although estimates of the Sharpe ratio of the global market portfolio over the period 1970–2022 are

[2]Real estate is the largest asset class in the world, but only a small fraction of it, which we capture, is available to financial investors. The value of all real estate in the developed world —including both the equity part and mortgages— amounted to US$217 trillion in 2015, according to Savills (2016). This number is about twice our estimate of US$104 trillion for the entire invested global multiasset market portfolio in 2015.

[3]We categorize cryptocurrencies as commodities broad. Similar to commodities, cryptocurrencies do not generate an autonomous yield, such as a dividend or interest income. Furthermore, like commodities, cryptocurrencies have to be mined, and some of them are (designed to be) scarce. Because of these characteristics some investors consider cryptocurrencies to be a safe haven asset and label them as 'digital gold' (see Nigro (2020)).

not much different from those on equity markets, and even lower than those of corporate bonds, they are more stable over time when investment horizons of a decade are considered. Hence, the confidence in a positive Sharpe ratio over a decade-long investment horizon, which could be an important decision criterion for investors, is higher for the global market portfolio than for individual asset categories, such as equities. This deepens the equity premium puzzle introduced by Mehra and Prescott (1985).

Our second contribution builds on the risk literature (see, e.g., Borsboom and Zeisberger (2020); Holzmeister et al. (2020)) that suggests investors care about the preservation of their capital. Using monthly return data, we estimate drawdown risk much more accurately than with annual data. If we subsequently adjust the average excess returns by maximum drawdown instead of volatility, the global market portfolio has the highest reward for risk. The global market portfolio also has the shortest maximum drawdown period. Again, given what we know about investors' perception of investment risk, the global market portfolio may be a better investment choice than individual asset categories.

For our third contribution, we examine the robustness of our choice of measurement currency, and we add nine other major currencies to our U.S. dollar returns. We observe substantial heterogeneity in the risk and reward of investing. The Sharpe ratio of the global market portfolio in U.S. dollars is the second highest of the ten and even highest when risk adjustment is based on maximum drawdowns. Without a clear theory explaining why the U.S. dollar should be the ultimate measurement currency for returns of the average investor, we might overestimate risk-to-reward ratios by exclusively using the U.S. dollar. Still, abstracting from trading costs, management fees, and taxes, returns on invested capital have on average been substantial, but one has to bear in mind that investors, compared to savers, have experienced deep and long drawdowns. Overall, we add risk dimensions to the discussion about the return on invested capital versus economic growth popularized by Piketty (2014). This is an important, as Barro (2023) finds that the return on (risky) equity has been above economic growth, but the return on (safe) bills is below.

In short, this study adds to the understanding of the risks of investing. This is relevant for macro economic analyses, but can also be used by investors for asset allocation and risk management.

This paper is organized as follows. Section 2 briefly describes the construction of the dataset. All data details have been relegated to the Online Appendix. Section 3 presents the results. Finally, Section 4 concludes.

2 Data

We define the market portfolio as all assets held by financial investors around the world. We add cryptocurrencies to Doeswijk et al. (2020), whose sample ends in 2017. As mentioned above, we categorize all asset classes into one of the five asset categories: equities broad, real estate, nongovernment bonds, government bonds broad, and commodities broad. We only include invested assets, leaving out assets that are not investable for financial investors, such as durable consumption goods, human capital, and family businesses. We also do not include 'emotional' assets, such as art (e.g., Goetzmann (1993), Mei and Moses (2002), Mandel (2009)), stamps (Dimson and Spaenjers (2011)), violins (Graddy and Margolis (2011)), wine (Dimson et al. (2015)), or whiskey (Tegtmeier (2022)). These markets tend to be opaque and relatively small in size compared to the markets that we cover. For example, the global art market was estimated to be smaller than $0.6 trillion in 2023.[4] Moreover, we derive returns from prices in financial markets only and do not rely on accounting-based or appraisal-based valuations that tend to lag prices on financial markets, and artificially reduce price volatility. By using market prices, we avoid underestimating investment risk.

We use as much as possible updated data from Doeswijk et al. (2014) and Doeswijk et al. (2020). However, their early historical data sources often report returns with an annual instead of monthly frequency. To estimate monthly returns, we therefore have to resort to alternative approaches or data sources. We describe these details in Online Appendix A. This allows for reproduction, extension, updates, replications, reexaminations, and reconciliations, following Welch (2019). The extensions and enhancements with respect to the earlier studies can be found in Online Appendix B.

Our default measurement currency is the U.S. dollar. However, we also discuss the impact of nine additional measurement currencies on our main results. To this end, we convert our U.S. dollar returns to other G10 currencies using historical exchange rates from MSCI. We focus on excess returns to put investing versus the alternative of saving. However, we also briefly discuss the results in real terms. Moreover, the real and nominal return time series of monthly returns for the global market portfolio in ten currencies are part of the dataset we have made publicly available.

We ideally calculate excess returns of investments relative to Treasury-bill yields, which proxy

[4]See, e.g., www.researchandmarkets.com/reports/5781146/arts-global-market-report.

for the return on savings.[5] Unfortunately, it is not possible to use a homogeneous definition across all countries, such as the three-month yields on Treasury bills in the secondary market, that we use for the United States. For three currencies, we resort to six-month yields, and for four countries we take high-quality yields or rates from non-central-government issuers for a part or for the whole sample period. We strive for a homogeneous series for each country. Differences across countries may affect comparisons of excess returns across countries to a certain extent, as there may be small but persistent term and credit risk premiums on the short end of the yield curve. Online Appendix C contains the risk-free rates that we use for each country.[6]

3 Empirical Results

3.1 Risk and Return Statistics

To start, Figure 1 shows the composition of the global market portfolio during our sample period of 1970–2022. Equities broad has been the largest asset category in the invested global market portfolio with an average weight of 49.7%, see Table 1. Its weight has varied from a minimum of 35.4% in February 2009 at the height of the credit crisis to a maximum of 63.5% in March 2000 at the peak of the dot-com bubble. The second-largest asset category is government bonds broad with a weight that has averaged 28.1% and has varied between 19.8% in November 1972 and 35.8% in July 1982, when equities started to recover after the deep recession of the early 1980s. While the asset category commodities broad is on average the smallest at 2.4%, its weight reached a maximum of 11.1% in February 1980, after the Hunt brothers cornered the silver market in 1979 (see Baker (2018)).

Figure 2 shows the cumulative total excess return indices for the global market portfolio and the five asset categories that are part of it. During our sample period, cumulative excess returns have been low or negative from 1970 to mid 1982, except for commodities broad, as witnessed by

[5]We define savings as cash and debt securities with a remaining maturity of fewer than 12 months. These are short-term safe assets, as in Gorton (2017). The quantity of safe assets over time has been estimated for the U.S. by Gorton et al. (2012) and internationally by Barro et al. (2022).

[6]However, bear in mind that lending money to another party always carries some risk of not receiving the full promised payment at maturity, even if it is a government or central bank that can decide to create extra money at will. Even cash that is not lent out is not risk-less in real terms in the presence of inflation shocks. Moreover, institutional investors may have long-dated pension or life insurance liabilities. For those investors, the 'risk-free' asset —the asset that minimizes their balance sheet risk— may be long-dated instead of short-dated fixed income instruments; see Klingler and Sundaresan (2019). The liability hedging property of long-dated bonds does however not mean they should be separated out of the market portfolio.

Figure 1. Composition of the global market portfolio

index values in mid 1982 that on balance have hardly changed since 1970. After the inflationary seventies a long stretched period of disinflation starts that runs to 2020, coinciding with positive cumulative excess returns.

Table 1. Composition of the invested global market portfolio (%)
Sample period January 1970 to December 2022. EB is the abbreviation for equities broad, RE for real estate, NGB for nongovernment bonds, GBB for government bonds broad and COM for commodities broad.

	EB	RE	NGB	GBB	COM
Average weight (%)	49.7	4.4	15.4	28.1	2.4
Minimum weight (%)	35.4	2.1	6.5	19.8	0.5
Median weight (%)	49.0	4.5	16.0	28.4	1.8
Maximum weight (%)	63.5	7.0	24.9	35.8	11.1
Weight dispersion (%)	28.1	4.9	18.4	16.0	10.6

The global market portfolio has an average monthly return in excess of cash of 0.34% with a standard deviation of 2.90%, see panel A in Table 2. The monthly excess return varies from a minimum of -13.6% (October 2008) to a maximum of 8.9% (January 1975). The monthly excess return is positive 58.8% of the time. Equities broad has an arithmetic average return of 0.51%, just

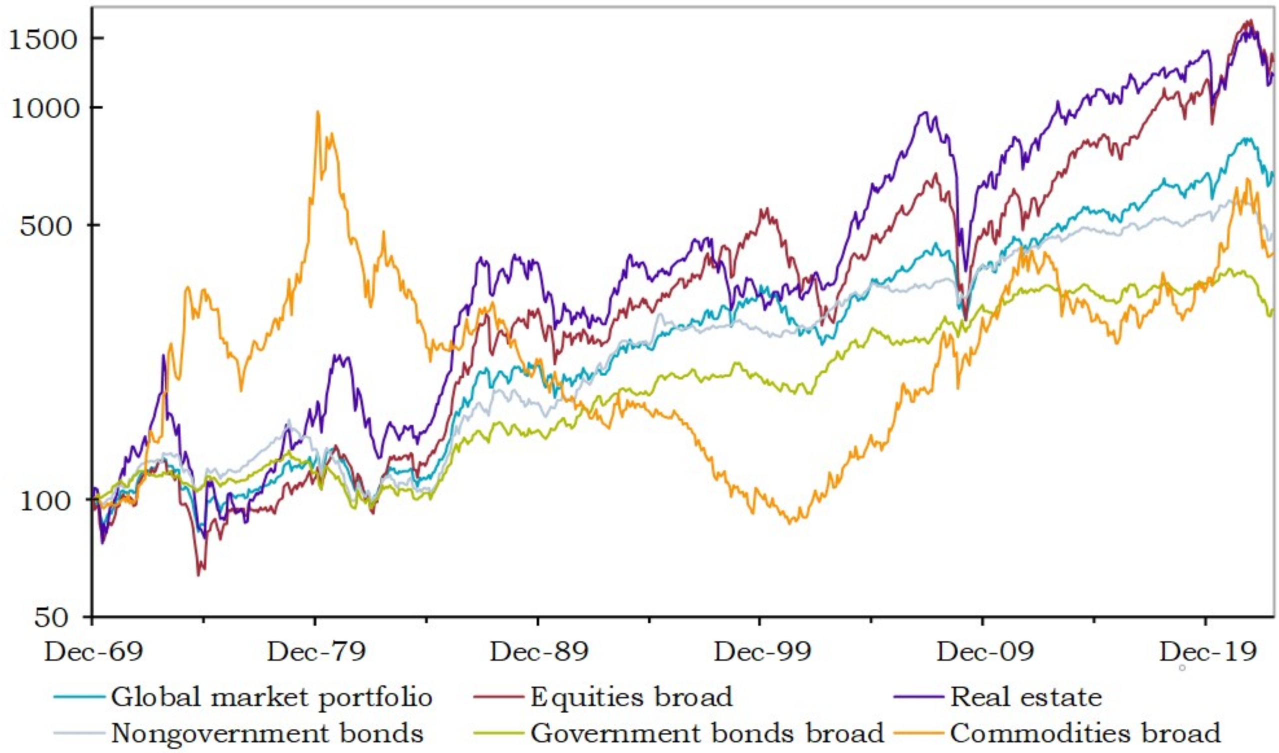

Figure 2. Cumulative total excess return indices for the global market portfolio and its asset categories (U.S. dollar; logarithmic y-axis)

below the 0.53% of real estate.[7] The average excess return for nongovernment bonds is 0.27%, with a standard deviation of 1.99%. The government bonds broad return is on average 0.19% with a standard deviation of 1.89%. Part of the government bond broad return is due to the term premium, and part is due to country default risk. Commodities broad has an average excess return of 0.40% with a large standard deviation of 5.87%, resulting in a compounded excess return of just 0.23%. These average returns line up with those reported in Doeswijk et al. (2020), although we start a decade later and extend the sample period by five years to 2022.[8]

The higher moments of the return distribution can also be important for risk analysis. First, we statistically test whether the monthly returns are normally distributed. Table 2 shows that the p-values of the Jarque and Bera (1987) tests are all 0.000. Thus, the null hypothesis that

[7]Because of its higher standard deviation, the compounded return for real estate is lower than that for equities broad. The wider return distribution is also visible for the extremes: the minimum monthly return for real estate is -24.75% and the maximum is 23.78%, while for equities broad this is -20.96% and 14.34%, respectively.

[8]The arithmetic excess of their global market portfolio over the period 1960–2017 is 3.98% per year, 6.24% for equities broad, 7.22% for real estate, 2.89% for nongovernment bonds, 2.01% for government bonds broad, and 3.74% for commodities. These annual returns can be compared to those in panel C of Table 2. Realized returns can also be compared with expected returns, for example those derived from options markets; see, e.g., Martin (2017).

Table 2. Composition and excess return characteristics of the invested global market portfolio
Sample period January 1970 to December 2022. Returns in U.S. dollar. GMP is the abbreviation for global market portfolio EB for equities broad, RE for real estate, NGB for nongovernment bonds, GBB for government bonds broad and COM for commodities broad.

	GMP	EB	RE	NGB	GBB	COM
Panel A: Excess return characteristics using *monthly* returns						
Compounded return (%)	0.30	0.41	0.39	0.25	0.18	0.23
Average return (%)	0.34	0.51	0.53	0.27	0.19	0.40
Standard deviation (%)	2.90	4.44	5.12	1.99	1.89	5.87
T-statistic	2.96	2.87	2.58	3.36	2.57	1.70
Minimum (%)	-13.63	-20.96	-24.75	-7.21	-6.00	-31.10
1st quartile (%)	-1.23	-2.01	-2.14	-0.70	-0.97	-2.89
Median (%)	0.55	0.81	0.90	0.23	0.21	0.15
3rd quartile (%)	2.11	2.94	3.25	1.23	1.35	3.14
Maximum (%)	8.89	14.34	23.78	8.47	7.68	32.45
Positive months (%)	58.8	59.4	59.6	57.2	54.7	51.1
Skewness	-0.54	-0.56	-0.44	0.03	0.07	0.69
Kurtosis	1.52	1.79	3.46	2.26	1.11	5.19
Autocorrelation	0.09	0.10	0.12	0.18	0.13	0.06
p-value normal distribution (JB)	0.000	0.000	0.000	0.000	0.000	0.000
Sharpe ratio	0.408	0.394	0.355	0.462	0.353	0.234
Avg. 10-yr rolling Sharpe ratios	0.461	0.441	0.409	0.575	0.417	0.101
St.dev. 10-yr rolling Sharpe ratios	0.204	0.222	0.214	0.312	0.273	0.474
Sharpe stability ratio	2.26	1.99	1.91	1.84	1.53	0.21
Panel B: Excess return characteristics using *calendar year* returns						
Compounded return (%)	3.65	4.97	4.81	2.98	2.13	2.76
Average return (%)	4.33	6.65	7.11	3.35	2.39	5.94
Standard deviation (%)	11.73	18.08	21.70	8.73	7.40	28.77
Skewness	-0.53	-0.63	-0.15	0.14	-0.08	2.09
Kurtosis	0.07	0.11	-0.37	0.17	0.06	8.31
Autocorrelation	-0.04	-0.13	-0.02	0.23	0.17	0.20
p-value normal distribution (JB)	0.286	0.175	0.780	0.890	0.966	0.000
Sharpe ratio	0.369	0.368	0.328	0.383	0.323	0.206

excess monthly returns follow a normal distribution is rejected for the global market portfolio and its components. The GMP has a skewness of -0.54, indicating that it has extreme or more observations on the left side of the distribution, and an excess kurtosis of 1.52, indicating fatter tails than the normal distribution. While the excess returns of each of the five asset categories also have fatter tails than the normal distribution, the skewness results differ. Nongovernment bonds and government bonds broad have skewness close to zero, while commodities broad has a positive skewness. Finally, the GMP and its components have small positive autocorrelations, suggesting that volatilities measured over a longer holding period may be higher than those measured at a monthly frequency. This is confirmed in Table 2 when we calculate volatilities for calendar year returns.[9]

Next, we compare whether the distributions obtained from return data at the monthly frequency differ from those obtained at the annual frequency reported in the previous literature. Since the excess kurtosis of the calendar year excess returns of the GMP are close to zero, the null hypothesis of normality cannot be rejected with a p-value of 0.286, consistent with Doeswijk et al. (2020). For the other asset categories, except commodities broad, we also cannot reject a normal distribution for calendar year excess returns. Notably, the skewness and kurtosis are higher for commodities broad for calendar years compared to monthly returns. The autocorrelations for the GMP turn from slightly positive at the monthly frequency (0.09) to slightly negative for calendar years (-0.04). A similar change can be seen for equities broad and real estate, but the three other asset categories show higher positive autocorrelations for annual returns, indicating that long-horizon risks may be even higher for these individual asset categories.

In sum, higher-frequency observations do not reveal more information about the average returns, but they give more information about the risks associated with investing. We explore the risk dimensions further in the remainder of this section.

3.2 Stability of the Sharpe Ratio

Calendar year and monthly returns lead to different Sharpe ratios, as shown in Table 2. The typical numerator is the *arithmetic* average excess return, and the denominator is the standard deviation of periodic returns. The annualized (using multiplication with a square root of 12) Sharpe ratios of monthly returns are, without exception, slightly above the ones calculated from calendar year returns. As Lo (2002) discusses, Sharpe ratios depend on the statistical properties of a return series. For example, monthly Sharpe ratios are overstated in the case of positive autocorrelation and understated in the case of negative autocorrelation. For the global market portfolio, the Sharpe ratio based on monthly returns is 0.408, while it is 0.369 for calendar year returns. This difference is approximately the same as the difference in volatility estimates, which in turn is partially due to the slight positive autocorrelation in monthly returns.

[9] Annualized monthly volatility for the GMP would be 10.04%, 15.39% for equities broad, 17.74% for real estate, 6.88% for nongovernment bonds, 6.56% for government bonds broad, and 20.32% for commodities.

Contrary to Modern Portfolio Theory, developed by Markowitz (1952), the global market portfolio does *not* have the maximum Sharpe ratio, despite its diversification across all globally invested assets. The Sharpe ratio of the global market portfolio, based on monthly returns, is 0.408. This is only slightly higher than the 0.394 of equities broad, but lower than the 0.462 of nongovernment bonds. The other asset categories have similar Sharpe ratios, except for commodities that only has a Sharpe ratio of 0.234. Note that these are full-sample estimated Sharpe ratios over the period January 1970 to December 2022.

The precision of risk estimates over a relevant investment horizon, such as a decade, diminishes with calendar year returns, leading to an increase in estimation errors. The monthly returns uncovered in this study enable us to more precisely estimate volatility risk over shorter periods. Consequently, we can relatively accurately examine estimated Sharpe ratios over rolling 10-year periods, starting at the end of 1979. Figure 3 displays these ratios, while Table 2 documents the statistics. Nongovernment bonds still have the highest average of 10-year rolling Sharpe ratios, while the global market portfolio remains second with an average of 0.461. The average subsample Sharpe ratios are higher than the Sharpe ratios over the full sample. This is to be expected, as volatilities are now calculated relative to subsample means instead of one full-sample mean.

Importantly, the global market portfolio has a relatively stable Sharpe ratio over 10-year rolling periods, as witnessed by the 0.204 standard deviation of 10-year rolling Sharpe ratios. Each component of the global market portfolio has a higher standard deviation of 10-year rolling Sharpe ratios, with nongovernment bonds having a standard deviation of more than 50% higher, at 0.312. Thus, the reward-to-risk fluctuates the least for the global market portfolio. Figure 3 displays rolling Sharpe ratios over time. During our sample period, the global market portfolio has a lowest 10-year Sharpe ratio of -0.131 in July 1982, and 16 months end with a negative 10-year Sharpe ratio. For nongovernment bonds, the lowest Sharpe ratio is -0.217 in June 1982, and 41 months end with a negative 10-year Sharpe ratio.

We divide the average 10-year Sharpe ratio by its standard deviation, which we call the Sharpe stability ratio. This statistic directly relates to statistical hypothesis testing, as a standard t-test on the null hypothesis that 10-year Sharpe ratios are equal to zero is a multiplication of the square root of the number of (independent) observations and the Sharpe stability ratio. The global market portfolio appears to have the highest Sharpe stability ratio at 2.26, see Table 2. Equities broad has the highest Sharpe ratio stability ratio of the individual asset categories with 1.99, followed by real estate with 1.91, and only then by nongovernment bonds with 1.84. In other words, the

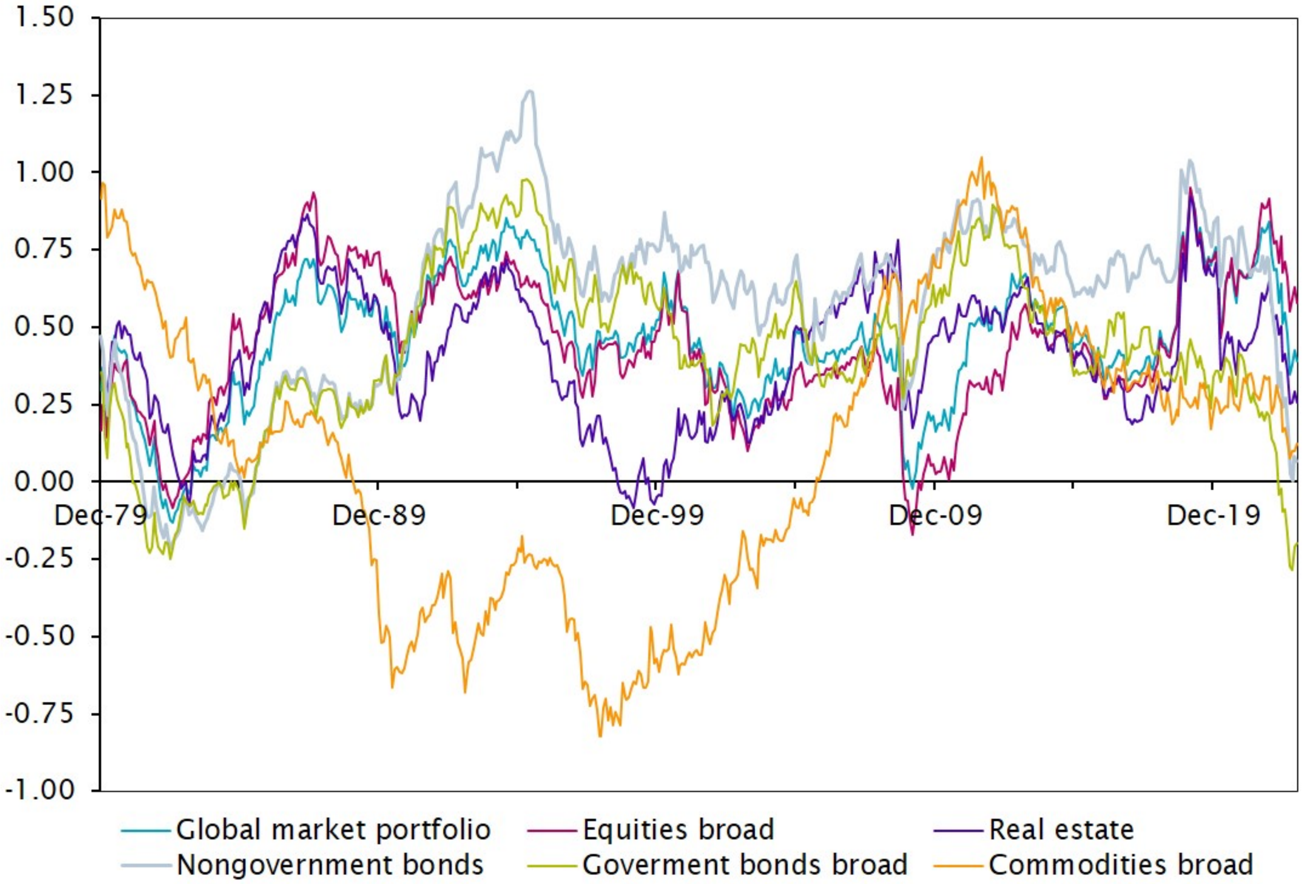

Figure 3. Sharpe ratios, rolling 120-month periods

average reward-to-risk ratio over 10-year periods is the highest for nongovernment bonds, but its Sharpe ratio varies relatively strongly between the (overlapping) 10-year periods we have in our sample period.

In summary, when the stability of the Sharpe ratio is taken into account, the global market portfolio performs better than each of the individual asset categories. This deepens the equity premium puzzle introduced by Mehra and Prescott (1985).

3.3 Drawdowns

A drawdown, the cumulative loss of an investment from peak to trough, is an important risk measure.[10] For many investors, capital preservation is important, and a drawdown expresses the risk of capital loss better than other statistics, such as volatility (see, e.g., Borsboom and Zeisberger

[10]Factually speaking, the market is in a drawdown unless it is at an all-time high. Measured in excess returns at the monthly frequency, the global market portfolio is in a drawdown 79.1% of the time.

(2020) and Holzmeister et al. (2020)). Drawdowns may have real economic consequences. For example, Ponds and Van Riel (2009) indicate that pension benefits may be cut when pension fund solvency is below a regulatory threshold, Riley and Yan (2022) find that mutual funds experience outflows after drawdowns, and Jen et al. (2007) suspect that large drawdowns can significantly affect the risk-taking appetite of sovereign wealth funds. Drawdowns can be manifestations of rare disaster risk, which may help explain the size of the equity premium (see, e.g., Barro (2006), Gabaix (2012), and Muir (2017)). Drawdowns also relate to macroeconomic conditions, as Barro and Ursúa (2017) estimate that the probability of a prolonged economic downturn increases after a stock-market crash.

Despite the practical importance of drawdowns, Van Hemert et al. (2020) and Alankar et al. (2023) observe that return characteristics in academic studies usually contain average returns and standard deviations, accompanied by other conventional measures like skewness, autocorrelation, and return factor loadings. However, these metrics do not capture the maximum drawdown as this follows from the sequence of returns. Given the large potential consequences of drawdowns, it is important to examine these in more detail in the context of the global market portfolio, that is, the drawdown that investors jointly experience.

Although drawdowns are not a default risk measure in finance journals, they have been discussed in the academic literature, see Geboers et al. (2023) for a system review. Probably the first mathematical analysis of a maximum drawdown is Taylor (1975), who uses a Brownian motion for stock prices. Bailey and López de Prado (2015) examine the effect of return autocorrelation on drawdowns. Grossman and Zhou (1993) use drawdowns as a constraint in portfolio optimization, while Zabarankin et al. (2014) analyze a capital asset pricing model with a drawdown measure. Landriault et al. (2015) extend the discussion on the severity of a drawdown to the frequency of drawdowns. Below, we will empirically analyze the maximum drawdown, the frequency of a drawdown with a prespecified size, and the duration of a drawdown.

Figure 4 shows drawdowns from the previous high in the excess return index for the global market portfolio and the two largest asset categories equities broad and government bonds broad. It clearly illustrates that sizeable drawdowns in the global market portfolio have mostly been in between those for equities broad and government bonds broad. Next, it shows that large drawdowns have not been uncommon for the global market portfolio.

Table 3 provides more insights into drawdown statistics for the global market portfolio and its five asset categories. The maximum drawdown of the global market portfolio is 36.0% with a

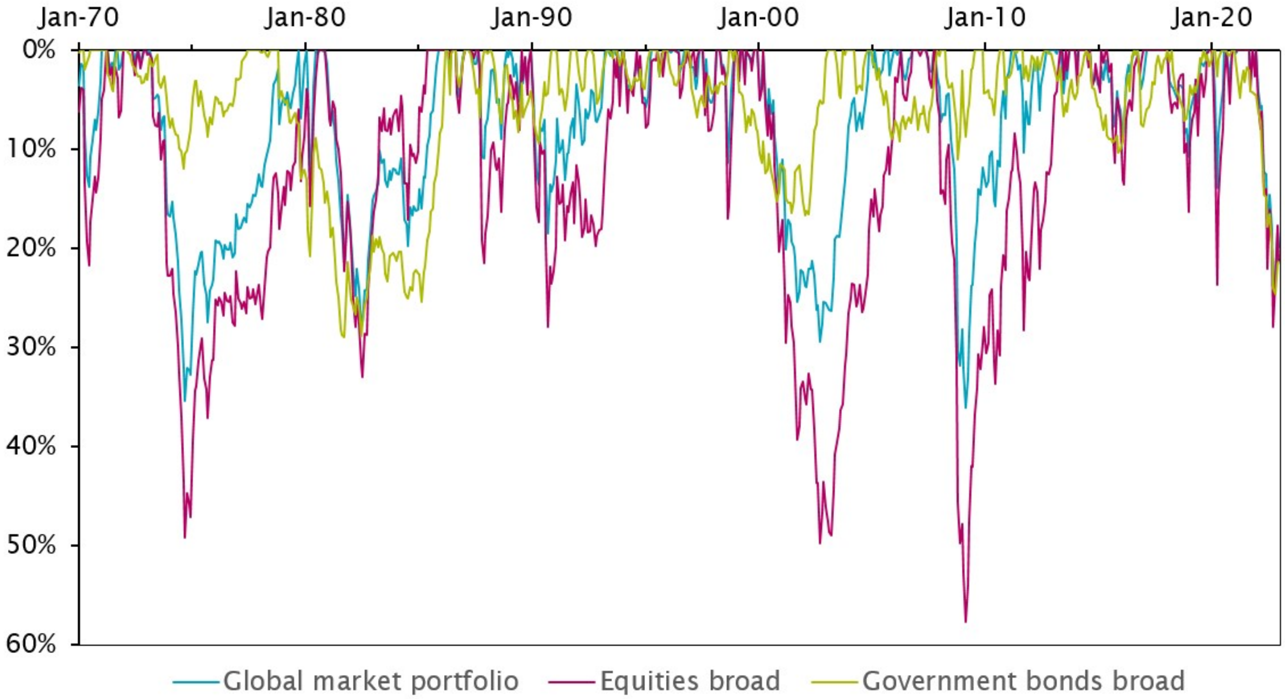

Figure 4. Drawdowns of the global market portfolio, equities broad, and government bonds broad

bottom in February 2009, see panel A. That is in between nongovernment bonds and government bonds broad. Nongovernment bonds have a maximum drawdown of 38.4% in June 1982, somewhat more than for the global market portfolio. Government bonds broad had the smallest drawdown at 28.9% in September 1981. Obviously, equities broad and real estate had deeper maximum drawdowns of 57.7% in February 2009 and 65.8% in December 1974. Commodities broad had a maximum drawdown of 91.1% in August 1999, but strictly speaking we have to add it concerns a preliminary number as this asset category has not set a new high yet.

We also calculate the ratio of the compounded average annual excess return divided by the maximum drawdown. We are not the first to relate investors' reward to maximum drawdown instead of standard deviation. This risk-adjusted return measure is often referred to as the Managed Accounts Report (MAR) ratio, after a newsletter founded in 1979 by Leon and Joy Rose.[11] The MAR ratio for the global market portfolio is 0.101. So, for each percentage point realized maximum drawdown, the investor has earned an annual 0.101 percentage point compounded excess return in our 53-year sample period. This is above the MAR ratios of all individual asset

[11]Source: www.marhedge.com [archive 12 January 1997]. The MAR ratio is typically calculated from inception of the portfolio, whereas a 36-month version of the ratio is often referred to as the Calmar Ratio by Young (1991).

Table 3. Drawdown statistics of excess returns and maximum duration of drawdown
Based on returns in U.S. dollar. GMP is the abbreviation for global market portfolio, EB for equities broad, RE for real estate, NGB for nongovernment bonds, GBB for government bonds broad and COM for commodities broad. The MAR ratio divides the compounded average annual return by the maximum drawdown.

	GMP	EB	RE	NG	GBB	COM
Panel A. Monthly data						
Maximum drawdown	36.0	57.7	65.8	38.4	28.9	91.1
Bottom date maximum drawdown	Feb-09	Feb-09	Dec-74	Jun-82	Sep-81	Aug-99
MAR ratio	0.101	0.086	0.073	0.078	0.073	0.030
Number of drawdowns >10%	13	12	11	6	6	4
Number of drawdowns >20%	5	9	9	3	2	2
Number of drawdowns >30%	2	4	5	1	0	2
Number of drawdowns >40%	0	3	3	0	0	2
Number of drawdowns >50%	0	1	2	0	0	1
Maximum duration of drawdown (months)	78	91	93	92	88	515
Panel B. Calendar year data						
Maximum drawdown	31.5	47.1	56.9	30.1	21.4	88.9
Bottom date maximum drawdown	1974	1974	1974	1984	1981	2001
MAR ratio	0.116	0.106	0.085	0.099	0.099	0.031
Number of drawdowns >10%	6	7	6	3	3	2
Number of drawdowns >20%	3	5	6	1	2	2
Number of drawdowns >30%	1	3	4	1	0	2
Number of drawdowns >40%	0	3	3	0	0	1
Number of drawdowns >50%	0	0	1	0	0	1
Maximum duration of drawdown (years)	6	7	7	7	7	43
Panel C. Differences for monthly versus annual data frequency						
Maximum drawdown	4.6	10.6	8.9	8.2	7.5	2.2
MAR ratio	-0.015	-0.019	-0.011	-0.021	-0.026	-0.001
Number of drawdowns >10%	7	5	5	3	3	2
Number of drawdowns >20%	2	4	3	2	0	0
Number of drawdowns >30%	1	1	1	0	0	0
Number of drawdowns >40%	0	0	0	0	0	1
Number of drawdowns >50%	0	1	1	0	0	0
Maximum duration of drawdown (months)	6	7	9	8	4	-1

categories, where equities broad is the asset category with the highest MAR ratio of 0.086, and commodities broad is the lowest at 0.030. So, when returns are adjusted for their maximum realized drawdown risk, the global market portfolio performs better than each of the individual asset classes.

Table 3 panel A also shows the frequency of drawdowns. During the sample period of 1970–2022, the global portfolio went through 13 drawdowns that exceeded 10%, five drawdowns exceeded 20%

and two passed 30%. Both equities broad and real estate experience drawdowns of 10% almost as often as the global market portfolio. For equities broad and real estate, deep drawdowns are not uncommon. Both have gone through three drawdowns in excess of 40%, and real estate has even gone through two drawdowns in excess of 50%. In fixed income, both asset categories have six drawdowns in excess of 10%, while nongovernment bonds once surpassed a drawdown of 30%. So, fixed-income asset categories have somewhat lower drawdown risk than the global market portfolio. Commodities broad can almost be described by a run-up until January 1980, followed by a huge drawdown until August 1999, followed by an ongoing recovery that does not reach the previous high by the end of our sample period.

In addition to the *severity* and the *frequency* of drawdowns, the *duration* of a drawdown matters. The time it takes to reach a new all-time high since the previous high is also important, as it says something about the recovery potential after a drawdown. Figure 5 displays the number of months since a previous high in the excess return index. In other words, it shows the period of a negative cumulative excess return of an investment in the global market portfolio made at the previous top in the excess return index. A drawdown duration of more than 60 months only happened once for the global market portfolio, but two more times 60 months almost has been touched. There are five points in time that were followed by a cumulative negative excess return for more than 36 months. It is also worth noting that all drawdowns other than the five mentioned before recovered within 24 months. This is likely well within the investment horizon of most investors.

Table 3 panel A shows that the maximum duration of a drawdown is 78 months for the global market portfolio. This is shorter than any of the individual asset categories that have maximum durations of drawdowns closely together in the range from 88 to 93 months, with commodities broad being the exception at 515 months, and counting.

The added value of monthly data is clear from our drawdown analysis. Annual returns tend to substantially underestimate drawdowns, particularly for individual asset categories. The maximum drawdown for the global market portfolio increases 4.6 percentage points when using monthly, instead of annual, data (see Table 3 panel C).[12] The increases in maximum drawdown for non-

[12]Moving from monthly to daily data would further increase the maximum drawdown, but we cannot reliably estimate this for the global market portfolio or most of its components. However, we can estimate the effect of using daily data by examining the MSCI All Countries World Index (the MSCI World Index before its inception in 1987). The maximum drawdown in the excess total return index increases from 47.2% with annual data to 55.4% with monthly data and to 58.8% with daily data, increases in maximum drawdown of 8.2 and 3.4 percentage points, respectively. So, for this index moving from annual to monthly data has a larger effect on drawdowns than moving

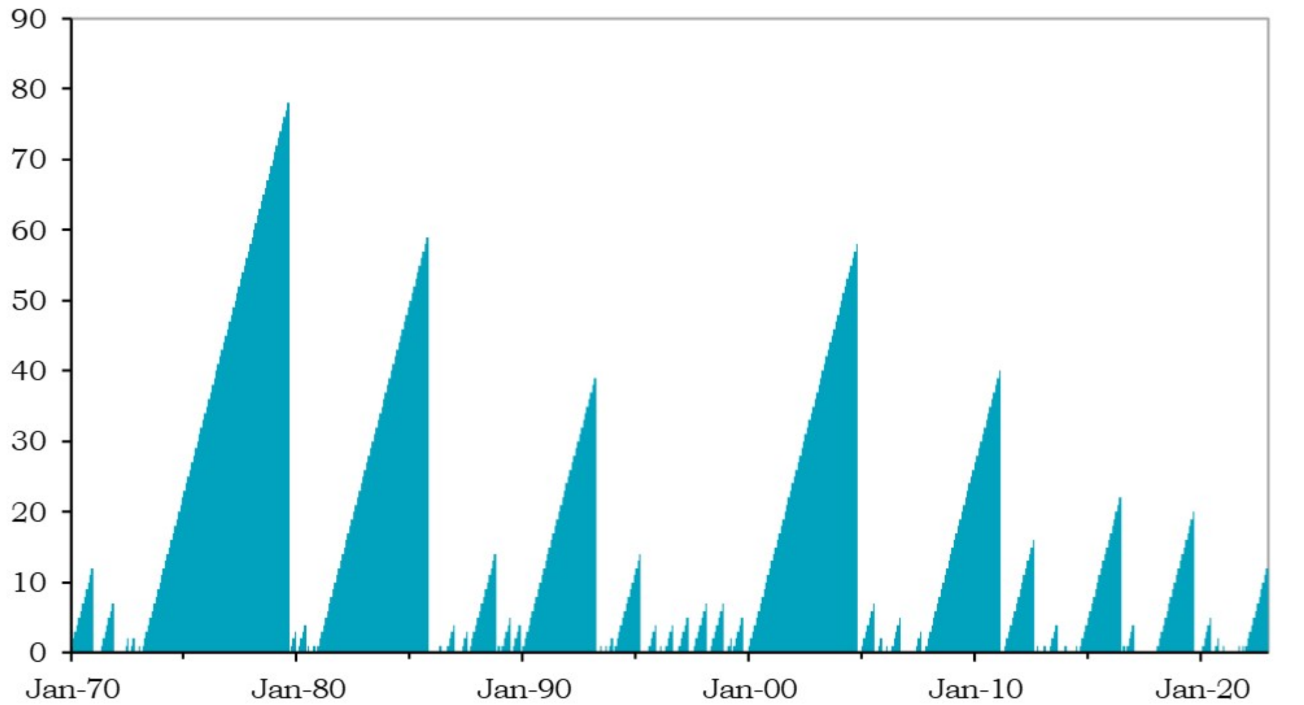

Figure 5. Duration of drawdowns for the global market portfolio (number of months)

government bonds and government bonds broad of 8.2 and 7.5 percentage points respectively, are large compared to equities broad and real estate, at increases of 10.6 and 8.9 percentage points respectively. It is remarkable that these increases are only slightly larger than for the less volatile fixed-income asset categories.

The added value of monthly data also appears from estimating the frequency of drawdowns. As appears from Table 3 panels A and B, the number of drawdowns exceeding 10% roughly doubles moving from annual data to monthly data in the global market portfolio and each of the asset categories. The maximum duration of a drawdown is affected less by moving from annual to monthly data, typically about six to nine months.

Our newly compiled monthly return database allows for a more accurate estimation of drawdowns. The drawdown analyses indicate that when average realized returns are adjusted for drawdown risks, the global market portfolio has a higher reward-to-risk ratio than each of the five asset categories. This suggests that diversification across asset classes can be valuable in mitigating investment risk.

from monthly to daily data. Moving from monthly to daily data for the global market portfolio is therefore unlikely to affect our drawdowns meaningfully.

3.4 Measurement Currency

We basically cover all assets around the globe that financial investors have invested in, so we are not prone to a selection bias toward a sample of countries or asset classes. However, consistent with most of the academic literature, we have chosen the U.S. dollar as our main measurement currency. This makes economic sense, as the U.S. dollar has been the world's reserve currency since at least World War II (see Eichengreen (2011)). However, it may also give a biased view of asset returns, as the U.S. dollar has been *the* ultimate safe-haven currency, which can affect return measurement. Therefore, we change the numeraire of return measurement to nine other major currencies that together with the U.S. dollar form the G10. Note that we are only changing the numeraire, so this subsection does not contain an analysis on optimal currency allocation (see, e.g., Campbell et al. (2010), nor does it link to international asset pricing models as in, for example, Adler and Dumas (1983) or Dumas and Solnik (1995). Although there is no generally accepted definition of safe-haven currencies, and the perceived safety of each currency may change over time, the U.S. dollar, Swiss franc, Japanese yen, British pound, and euro are generally considered to be safer than the other currencies that make up the G10.[13] The correlation between currency and financial market returns, in combination with differences in short-term interest rates and inflation, can lead to not only different average excess and real returns in different measurement currencies but also different volatility and drawdown risks.

Measuring financial history in U.S. dollars, compared with other currencies, generates above-average excess returns with lower risk. Table 4 shows the excess return characteristics of the global market portfolio across ten currencies. For each measure, we also show the unweighted average and the dispersion between the highest and lowest observations.

The compounded excess monthly returns measured in U.S. dollars are five basis points above the average for the ten currencies. The compounded excess returns measured in Swedish krona are highest and 15 basis points per month above those measured in New Zealand dollars, which is the measurement currency with the lowest excess returns. On an annual basis, the difference is 1.88%, more than half the size of the average excess return observed in U.S. dollars.

The standard deviation of monthly excess returns of the global market portfolio is 2.90% measured in U.S. dollars, somewhat below the average of 3.04%. There is a dispersion of 0.86%

[13] For a more detailed discussion of safe-haven currencies, see, for example, Ranaldo and Söderlind (2010), Habib and Stracca (2012), and Klingler and Lando (2018).

Table 4. Risk and reward of the global market portfolio measured in G10 currencies (1970–2022) Compounded return, average return, volatility, median, minimum, maximum, maximum DD at monthly data and maximum DD at annual data in percentages, DD > x% are counts, DD duration, and the Sharpe and MAR ratio don't have units. The MAR ratio divides the compounded average annual return by the maximum DD. DD is the abbreviation for drawdown.

	AUD	CAD	EUR	JPY	NZD	NOK	SEK	CHF	GBP	USD	AVG	DISP
Comp. return	0.20	0.26	0.22	0.30	0.18	0.18	0.33	0.23	0.27	0.30	0.25	0.15
Avg. return	0.25	0.29	0.27	0.36	0.23	0.22	0.37	0.29	0.32	0.34	0.29	0.15
Volatility	3.05	2.55	3.05	3.42	3.24	2.87	2.95	3.40	3.01	2.90	3.04	0.86
Median	0.22	0.29	0.48	0.67	0.15	0.23	0.44	0.65	0.37	0.55	0.41	0.53
Minimum	-9.4	-8.8	-14.1	-20.0	-10.3	-11.4	-12.1	-14.6	-14.0	-13.6	-12.8	11.2
Maximum	21.5	9.7	12.6	9.1	24.8	9.9	22.7	10.8	12.3	8.9	14.2	15.9
Sharpe ratio	0.280	0.393	0.308	0.362	0.242	0.270	0.435	0.290	0.363	0.408	0.335	0.193
Max DD mth	50.1	34.9	49.5	46.8	55.2	48.0	38.0	52.7	36.8	36.0	44.8	20.4
Max DD ann	45.5	30.5	49.5	38.9	46.8	48.0	38.0	51.7	35.2	31.5	41.6	21.2
MAR ratio	0.049	0.090	0.055	0.078	0.038	0.046	0.105	0.052	0.089	0.101	0.070	0.067
DD > 10%	7	7	10	9	5	7	8	11	8	13	9	8
DD > 20%	4	4	3	4	3	3	3	5	4	5	4	2
DD > 30%	3	3	3	3	3	3	3	4	3	2	3	2
DD > 40%	3	0	2	1	1	2	0	1	0	0	1	3
DD > 50%	1	0	0	0	1	0	0	1	0	0	0	1
Max DD dur.	225	163	164	137	267	170	158	140	121	78	162	189

in standard deviations. The differences in average excess returns and in the standard deviations lead the Sharpe ratios of the global market portfolio to range between 0.242 (New Zealand dollar) and 0.435 (Swedish krona). In other words, the reward for standard deviation risk measured in Swedish krona is almost double when measured in New Zealand dollars. The Sharpe ratio in U.S. dollars of 0.408 is the second highest. It is important to realize that risk-adjusted returns measured in U.S. dollars may be substantially different, and mostly higher, from those in other major currencies.

When we shift our attention to drawdown risk, we see a similar pattern of huge differences between results in different measurement currencies for both the minimum excess return in a month and the maximum drawdown. As an illustration, consider how the minimum monthly excess return of the global market portfolio has a dispersion of 11.2%, and varies from -8.8% (Canadian dollar) to -20.0% (Japanese yen), whereas measured in U.S. dollars it is slightly above average with -13.6%.

The maximum drawdown of the global market portfolio measured in U.S. dollars of 36.0% is 8.7% smaller than the average maximum drawdown of 44.8%. Measuring the maximum cumulative loss in invested financial wealth across the world paints another picture than measuring it in most other currencies. In euros it is 49.5%, in Swiss francs 52.7% and in New Zealand dollars even 55.2%. The maximum drawdown period measured in U.S. dollars was 78 months, which is the lowest compared to the nine other measurement currencies. The average maximum drawdown period is well over 10 years. This clearly shows that considering the risk of investing by using long-term historical risk measured in U.S. dollars can lead to substantial underestimation of actual historical risk. Similar to the Sharpe ratio, the MAR ratio in U.S. dollars of 0.101 is well above the average of 0.070.

As mentioned before, the definition of risk-free rate differs among measurement currencies and can affect results. However, with real returns the dispersion in outcomes hardly changes, and risk-adjusted real rates of returns in U.S. dollar remain above average.[14] Real returns in U.S. dollar are just marginally above average, but both the standard deviation and the maximum drawdown are below average. This results in the fourth-highest ("Sharpe") ratio of the average real return to its standard deviation and the third-highest MAR ratio. The maximum duration of a drawdown in U.S. dollars is closer to average but still below average. Online Appendix D contains tables with real and nominal return characteristics, although nominal returns are less suitable for a comparison of results in different measurement currencies. We add outcomes in nominal returns to provide readers with a complete overview.

4 Conclusions

This is the first study documenting the historical risks and rewards of the aggregate investor in global financial markets by studying *monthly* returns. Our sample period runs from January 1970 to December 2022. The breadth of asset classes in this study is unmatched as it basically covers all accessible financial investments of investors across the world. Although the increase in return frequency from annual to monthly does not affect the measurement of average returns, it does allow for more precise estimation of the risks involved with investing. Our work extends the seminal work of Jordà et al. (2019) by further exploring the dimension of investment risk.

Despite its diversification across all globally invested assets, the global market portfolio does not have the highest Sharpe ratio compared to the five asset categories over our 53-year sample period. Its Sharpe ratio is only slightly higher than that of equities broad, but lower than that of nongovernment bonds. However, our newly collected monthly return data allows us to examine

[14] In Online Appendix A we discuss how we derive real returns.

the time variation of the Sharpe ratios of the five asset categories and the global market portfolio. The stability of the Sharpe ratio over rolling decade samples is substantially greater than that of individual asset categories. In other words, confidence in a positive Sharpe ratio for the global market portfolio over a decade is highest. Access to monthly returns is crucial for such assessment.

The risk literature suggests that investors care about the preservation of their capital. Monthly return data allows us to estimate drawdown risk much more accurately. If we adjust the average returns by drawdowns instead of volatility, the global market portfolio has the highest reward for risk, and the shortest maximum drawdown period.

All of the results above have been measured in U.S. dollars. If we change the measurement currency to one of the nine other major currencies, we observe substantial heterogeneity in the risks and rewards of investing. The Sharpe ratio of the global market portfolio in U.S. dollars is the second highest of the ten, and even highest when the risk adjustment is based on the maximum drawdowns. Hence, assuming that investors with other base currencies can achieve the risks and rewards that follow from U.S.-dollar-based analysis may not be justifiable.

Overall, our new monthly data on the global market portfolio suggests that the aggregate investor has experienced considerable wealth losses compared to savers who earn a nominal risk-free interest rate. Such losses are usually recovered within five years, but recovery can take substantially longer. Diversifying across asset classes reduces investment risk.

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Online Appendices

A Monthly Returns Data

We use the calendar year-end market capitalizations to calculate the return of the global market portfolio in January. Subsequently we use market capitalizations based on buy and hold with reinvested dividends for the subsequent eleven months. This way, the annual returns of the market portfolio coincide with the product of twelve monthly returns. We realize that differences in dividend payments, buybacks, redemptions, and issuance will lead to small differences between our approach and the true market capitalizations at each month-end. However, the latter are not always available. All differences in net issuance during the year are reset at every year-end, where we have market capitalization estimates available.

We use as much as possible updated data from Doeswijk et al. (2020). However, their early historical data sources often report returns with an annual instead of monthly frequency. To estimate monthly returns, we therefore have to resort to alternative approaches or data sources. Below, we describe alternative approaches in detail. For periods or asset classes that we do not mention below, we refer to the sources mentioned in Doeswijk et al. (2020) as we would otherwise get a lengthy appendix.

In addition to including cryptocurrencies, there are five additional small enhancements that result from minor changes in data compared to Doeswijk et al. (2014) and Doeswijk et al. (2020). These enhancements concern (1) market capitalization of real estate over the period 1970–1998, (2) market capitalization of high-yield bonds over the period 1997–2001, (3) government bond market capitalization over the period 2001–2005 and returns over the period 1970–1984, (4) maturities of global corporate bonds over the period 1975–1977, and (5) adjustment of the free float for investment-grade credits and government bonds. These five enhancements have limited impact on the composition and returns of the global market portfolio. That also applies to including cryptocurrencies. Appendix B contains all details for reproducibility.

The measurement currency in this paper is the U.S. dollar. However, we also discuss the impact of different measurement currencies on our main results. We calculate the return series for the invested global market portfolio in ten currencies, using exchange rates from MSCI.[15] To arrive

[15] The nine additional currencies are the Australian dollar, Canadian dollar, European euro (German mark before 1999), Japanese yen, New Zealand dollar, Norwegian Krone, Swedish krona, Swiss franc, and the Great British Pound Sterling. The data codes for these series are MSERAUD, MSERCAD, MSEREUR (before 1999 MSERDEM), MSERJPY, and MSERNZD before 1982 deducted from NZDOLLR, MSERNOK, MSERSEK, MSERCHF, and MSERGBP, respectively.

at real return indices, we use the non-seasonally-adjusted consumer prices indices for all items from the OECD for each of the countries, which we source from FRED.[16] For the Eurozone we use the inflation data for the eurozone[17] from 1999, and before we use the consumer price index of Germany. For each year we calculate the compounded monthly inflation from the December year-over-year inflation rate. We apply the same compounded monthly inflation rate to all months in a given year.

A.1 Equities

Doeswijk et al. (2020) use the MSCI World Index as their primary source for annual global equity returns. However, before 1985 they switch to the annual returns reported by Ibbotson et al. (1985) as it covers a larger universe than the MSCI World Index. However, the disadvantage of Ibbotson et al. (1985) compared to MSCI World is that the former do not report monthly returns. Since we want monthly returns that add to the annual returns of Ibbotson et al. (1985), we transform the monthly returns of the MSCI World Index for the period before 1985. For each year, we determine a fixed return adjustment that we apply to each of the twelve monthly returns in a particular year. We set the value of the return adjustment such that the adjusted compounded monthly returns from the MSCI World Index geometrically multiply to the annual return from Ibbotson et al. (1985). This way, the annual calendar year returns that follow from our monthly return series match the annual returns that follow from the original annual data series. The formula below illustrates this approach:

$$\widehat{MR}_{m,t} = (1 + MR^{MSCI}_{m,t}) \times \left(\frac{1 + AR^{ISL85}_t}{1 + AR^{MSCI}_t} \right)^{\frac{1}{12}} - 1 \tag{1}$$

where $\widehat{MR}_{i,t}$ is the estimated total return of month m in year t, $MR^{MSCI}_{i,t}$ the monthly total return of the MSCI World Index for month m in year t, $1 + AR^{ISL85}_t$ the annual total return of original data source Ibbotson et al. (1985) in year t, and AR^{MSCI}_t the annual total return of the MSCI World Index in year t. As an example, the equity return from Ibbotson et al. (1985) is -3.07% in 1970, while the MSCI World Index returns -1.98%, a difference of -1.09%. The January

[16]The data code for these series are AUSCPIALLQINMEI, CPALCY01CAM661N, CP0000EZCCM086NEST (DEUCPIALLMINMEI before 1999), CPALCY01JPM661N, NZLCPIALLQINMEI, NORCPIALLMINMEI, SWECPIALLMINMEI, CHECPIALLMINMEI, GBRCPIALLMINMEI, and CPALTT01USM657N.

[17]We use the consumer price index that expands the number of countries through time instead of the index that takes all current eurozone members into account since 1999.

total return of the MSCI World Index is -5.47% in January 1970. We adjust the return for global equities for January 1970 to -5.56%, which follows from Equation (1). Over 12 months, the monthly adjustments of -0.09% geometrically add to the full year difference in calendar returns between both sources. We adjust the returns of the MSCI World Index because the equity return of Ibbotson et al. (1985) better represents the asset class due to a larger universe of stocks.

A.2 Real Estate

Real estate data sources in Doeswijk et al. (2020) have a monthly frequency available since 1972. For non-U.S. data, monthly observations start in 1970. For the U.S. they compose a synthetic U.S. residential real estate investment trust (REIT) index before 1972 to estimate the returns on invested real estate, arguing that the correlation between residential REITs and the broader U.S. REIT market is 0.90 in the 1994–2017 period. However, it has come to our attention that there is a discontinued S&P Real Estate Investment Trust Index available in Global Financial Data from January 1969 to January 1992. This concerns a price index that lacks total return data. Nevertheless, this index would have been valuable for 1970 and 1971 as the correlations of annual price returns between this index and the FTSE NAREIT Equity REIT Index that Doeswijk et al. (2020) use for the U.S. from 1972 is 0.85 in the overlapping years 1972 to 1991.

In this study we use the price returns from the S&P Real Estate Investment Trust Index. For the dividend return in each month in both 1970 and 1971 we suppose it to equal the dividend return of the FTSE NAREIT Equity REIT Index in that same month in 1972. This seems to be a reasonable assumption, because the price return of the S&P REIT Index is limited in both years, while underlying rental income in real estate tends to move gradually outside recessions. Moreover, the dividend return of the closely related S&P 500 index in 1970 and 1971 is just a little bit above the dividend return in 1972.[18]

Estimation errors in our return estimates for U.S. real estate are depressed at the aggregate level by the small weight of U.S. real estate in the global market portfolio: 1.6% at the end of 1969. Moreover, as Doeswijk et al. (2020) point out, the estimation error at the aggregate level further benefits of diversification of estimation errors in return estimates of asset classes.

[18] According to Damodaran Online the S&P recorded a dividend of 3.5% and 3.1% in 1970 and 1971, respectively. In 1972 the dividend yield was 2.7%.

A.3 Government Bonds

For the period after 1985, we use the same data sources as Doeswijk et al. (2020) to obtain monthly returns: Bloomberg Multiverse Government Index back until 2000 (float-adjusted after 2010), thereafter Bloomberg Global Treasuries Index back to 1987, and thereafter the FTSE World Government Bond Index for 1985 and 1986. Prior to 1985, they use annual data from Ibbotson et al. (1985). As these authors do not report monthly data, we need an alternative source. To this end, we extend the FTSE World Government Bond Index further in history by using a similar approach. We apply our methodology also over the period 1985 to 1990, such that there is a 72 month overlap between our data and methodology, and the official published index. This overlapping period is used to determine how close both return series are.

Our first step is determining the index weights. We convert government debt amounts to U.S. dollars for market capitalization-based index weights.[19] We use data on GDP and debt-to-GDP ratios to calculate debt amounts by multiplying both. Our main source for GDP data in U.S. dollars is the World Bank. For GDP data of Switzerland, the World Bank has missing data for the period 1970–1979. We use OECD data for this period. For Germany, the World Bank has no observation for 1969. Here, we use the GDP growth rate in 1969 from Global Price and Income History Group to arrive at the 1969 GDP using the World Bank's 1970 data point.[20] We need the 1969 GDP as input to derive calendar year-end market capitalizations in 1969, that we use to calculate the return of the global government bond market in January 1970.

We use central government debt-to-GDP ratios from Reinhart and Rogoff (2011).[21] They focus on gross central government debt as time series for other broader measures of government debt are not available for many countries. This ensures consistent estimates of government debt for all countries. However, they do not have central government debt data for the Netherlands, but they do provide the general government debt-to-GDP ratio that we do use in our analysis. This means that we overestimate the amount of debt for the Netherlands.[22] However, as the GDP is small

[19] We estimate the nominal value of outstanding debt instead of debt at market prices. But nominal government debt relative to other countries and the market value of government bonds relative to other countries should ex-ante be highly correlated, because interest rates tend to show parallel movements and governments tend to issue predominantly coupon-bearing bonds at market interest rates.

[20] Available online: gpih.ucdavis.edu. We do not adjust for currency movements as these were limited under Bretton Woods.

[21] See Debt-to-GDP Ratios - Carmen Reinhart. For Switzerland, the debt-to-GDP ratio is missing in 1984 and 1985. Here, we linearly interpolate.

[22] The International Monetary Fund (IMF) also has debt-to-GDP ratios. Unfortunately, the IMF's database does not have a consistent definition of public debt across countries, especially before 1980, see Abbas et al. (2010).

relative to other countries, this has only a small effect on the results.

Our second step is calculating the index returns. For this purpose, we collect government bond yield data for the nine countries that are part of the FTSE World Government Bond Index in 1985. As we target the return of the whole government bond market, we prefer bond yields with a maturity of around five as this is likely to be closer to the market's maturity than benchmark bonds with a maturity of ten. For example, the average maturity of the Bloomberg U.S. Treasury Index is 5.4 for the period 1973–1984. If there is no data on 5-year bonds, we use the closest available alternative. We follow Doeswijk et al. (2020) to calculate local currency returns. We use exchange rates from MSCI to convert the local currency returns into U.S. dollar returns.

Table A1 contains the start dates for end-of-month yields that we use, the maturity of the yield series and the data source. For observations that we miss, we use the 10-year government bond yields of the OECD from December 1969 until the yields shown are available. According to the OECD (1981), interest rates provided are generally monthly averages instead of end-of-month data. However, Table A1 shows that we have end-of-month yield observations for most countries from 1970 onwards. Figure A1 shows the different types of bond yields that we use in terms of market capitalization. Here, "Close to end-of-month" refers to the last Wednesday of a month. This applies to Canada. Before 1978, on average 82.3% of the index is based on end-of-month yields. Subsequently, this average is 89.0% for the period up to 1984. From 1985, the average increases to 93.3%. We use the returns from 1985 only to compare our index to the FTSE World Government Bond Index.

The third and final step is to combine the index weights and the U.S. dollar returns for the countries in our sample into a market capitalization weighted total return government bond index. We label this our basic global government bond index. As Table A2 shows, the basic index that we calculate is similar to the FTSE WGBI. Over the period January 1985 to December 1990, the returns of our basic index have a correlation of 0.99 with those of the FTSE WGBI, while the compounded return of 1.10% hardly differs from the 1.14% for the FTSE WGBI. The average of the absolute differences between the monthly returns of both indices is 0.27%, which is small compared to the standard deviation of monthly returns of 2.34% for the FTSE WGBI over this period.

When we replace the returns that we calculate for the U.S. with those of the Bloomberg U.S. Treasury Index, the results come marginally closer to the FTSE WGBI Index, on all statistics

Therefore, we prefer data from Reinhart and Rogoff.

Table A1. Availability of end-of-month government bond yields data, used maturity and source by country (1970–1990)

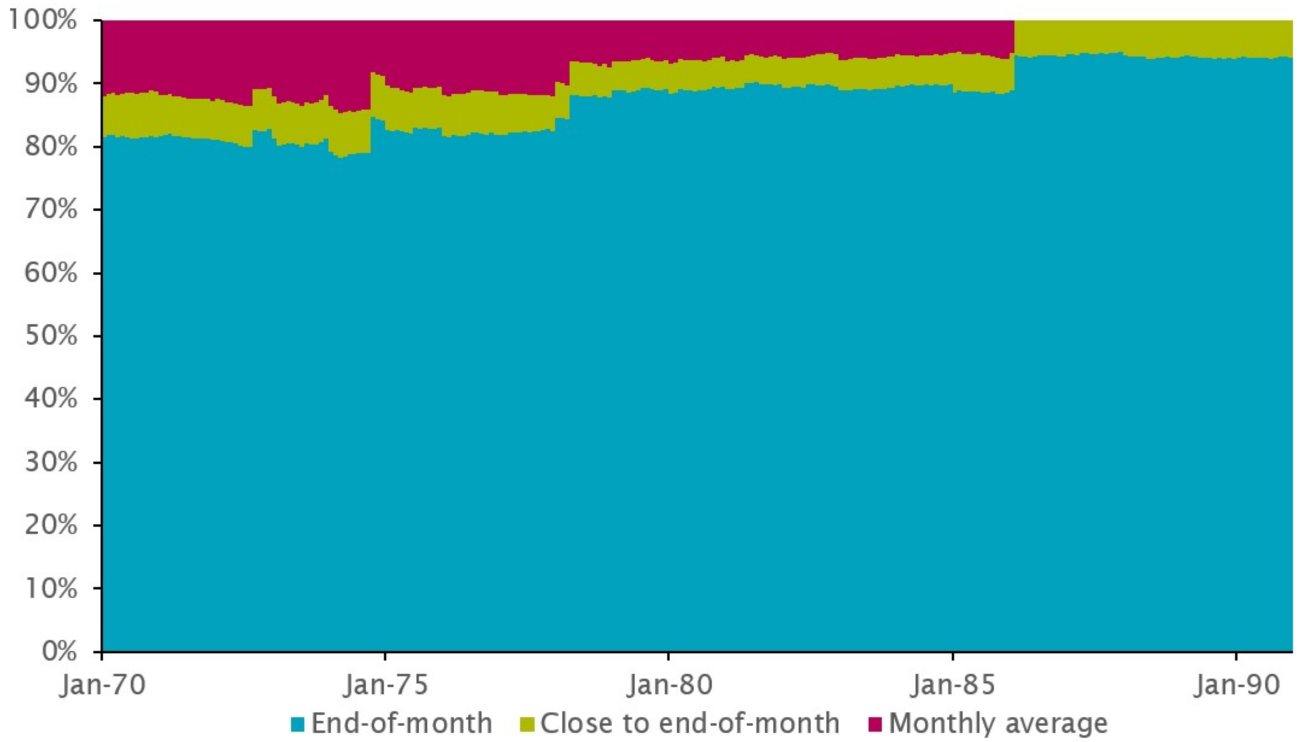
Country	Start	Maturity	Source
Australia	Dec 71	10	Reserve Bank of Australia
	Jan 72	5	
Canada	Dec 69	5-10	Statistics Canada
	Nov 80	5	
France	Feb 86	10	Refinitiv Datastream - FRBRYLD(RY)
Germany	Dec 69	5	Monthly reports of the Deutsche Bundesbank
	Sep 72	5	Deutsche Bundesbank website
Japan	Sep 74	5	Bank of Japan
Netherlands	Apr 78	10	Refinitiv Datastream - NLBRYLD(RY)
Switzerland	Dec 69	5	Swiss National Bank – at request
	Jan 77	5-12	
	Jan 84	>5	
United Kingdom	Jan 70	10	Thomas, R. and N. Dimsdale (2017), "A Millennium of UK Data", Bank of England
United States	Dec 69	5	Federal Reserve

Canada concerns data for last Wednesday of each month. Next, for Canada we use a maturity of 7 in our return calculations for the period January 1970 to November 1980. For Switzerland we use a maturity of 8 in our return calculations from February 1977 onward.

reported in Table A2. Finally, when we adjust monthly returns of our index to ensure that annual calendar year returns of our index equal those of the FTSE WGBI, the average returns by definition equal the average returns of the FTSE WGBI, but other statistics do not come closer. This further illustrates that such an adjustment hardly improves our government bond index with Bloomberg U.S. Treasury Index.

Taken together, the results show that our self-created index is a very close proxy to the FTSE published index. Our index before 1985 uses U.S. returns from Bloomberg and non-U.S. returns derived from government bond yields as explained above. In contrast to equity returns, we do not correct our monthly returns to ensure that annual returns match the global government bond returns that Doeswijk et al. (2020) source from Ibbotson et al. (1985) before 1985. Our return series uses actual government bond maturities of the collected bond yields and should therefore be more accurate than the Ibbotson et al. (1985) series that are based on estimated maturities.

Figure A1. Government bonds yield data (1970–1990)



A.4 Investment-Grade Credits

For the asset class investment-grade credits Doeswijk et al. (2020) use data sources with monthly frequency from 1997 that we also use in this study. Prior to 1997, they use hand-collected annual yield data from nondigitalized OECD Financial Statistics books to construct a global corporate bond index. They perform an additional analysis which suggests that returns on corporate bonds are a fair estimate for the returns of the whole asset class investment-grade securities for the period up to 1996. In this study, we also use the same OECD books to hand-collect monthly bond yields. However, there are months with missing data observations as the reporting period in OECD books sometimes cover different months. Unfortunately, months sometimes overlap or do not connect. To maximize the number of observations, we adjust our data collection process.

To construct an uninterrupted time series of corporate bond returns for a country, we follow the following waterfall procedure for each month. Our primary source for corporate bond yields is the central bank or the national statistics office. If those are not available, we take them from the OECD books. Next, we check the statistical appendices to various editions of the Annual Report

Table A2. Monthly returns for global government bond indices (US$, 1985–1990)

	Our basic index (1)	Our index with Bloomberg U.S. Treasury returns (2)	Our adjusted index with Bloomberg U.S. Treasury returns (3)	FTSE WGBI (4)
Compounded return (%)	1.10	1.12	1.14	1.14
Average return (%)	1.13	1.14	1.17	1.17
Median return (%)	1.27	1.28	1.30	1.41
Standard deviation	2.33	2.33	2.33	2.34
Maximum (%)	6.45	6.65	6.65	6.74
Minimum (%)	-3.74	-3.94	-3.94	-3.99
Avg. absolute difference vs. FTSE WGBI	0.27	0.26	0.26	
Correlation with FTSE WGBI	0.99	0.99	0.99	

Our basic index is solely based on return estimates derived from collected bond yields and maturities. In the second index we replace our derived U.S. returns with Bloomberg U.S. Treasury returns. The third index forces the annual return of second index to equal the FTSE WGBI by compressing or enlarging all monthly returns.

of the Bank of Italy. These appendices contain corporate bond yields for a varying group of 6 to 11 countries around the world. These data are available until March 1982. The last source we use for corporate bond yields is the Monthly General Statistics Bulletin 12-1976 from Eurostat. This publication contains private sector bond yields for some European countries for the period 1975 to 1978 and is useful to fill some gaps for the Netherlands and France.

This still leads to a few missing observations. To tackle these, we resort to two additional derivations. First, we use linear interpolation of the risk premium of corporate bonds relative to government bonds to estimate the risk premium. We add the interpolated risk premium to the government bond yield for the month(s) it concerns. We use government bond yields with a maturity that comes closest to the maturities of the corporate bonds, depending on data availability. Still, there are missing observations for some months for Austria and Spain in years that do have annual returns available in Doeswijk et al. (2020). Then, we use the local currency return of the market capitalization weighted return of the global corporate bond portfolio without these countries.[23]

[23] This way, we still take the currency return into account. This applies to the period from January 1975 through

The U.S. is the only exception to the described process of calculating monthly returns. We use actual returns of the Bloomberg U.S. Aggregate Corporate Index instead of estimating them based on corporate bond yields. Before 1973 we use the Long-Term Corporate Bond Index in Ibbotson (2015).

Table A3 shows that four of the nine countries that we source from the OECD have end-of-month observations or an observation on a day that is close to month end. We do not show the United Kingdom and the United States in this table. For the United Kingdom we use end-of-month yields from the Bank of England. For the United States we do not calculate returns ourselves, but the actual returns we use are by definition based on end-of-month yields. For Canada we use end-of-month yields from 1970 until 1988.

Table A3. Data observation types for corporate bond yields from the OECD

Country	Bond yield according to OECD
Austria	Monthly average
Belgium	First day of following month
Canada (after 1988)	End of month
France	Last Friday of month
Germany	Monthly average
Italy	Monthly average
Japan	End of month
Netherlands	Monthly average
Spain	Monthly average

To optimize the series of corporate bond yields for use in calculating monthly bond returns, we adjust the time series of some countries to come closer to end-of-month yields. We add the difference between the end-of-month yield on government bonds and the government bond yield that we calculate based on the definition that is in place for a particular country. To illustrate, for Germany we add the difference between the end-of-month government bond yield and the average government bond yield during that month to the corporate bond yield.[24] In other words, we use the average risk premium of corporate bonds relative to government bonds, and we add it to the

June 1975 for both Austria and Spain. For Spain, we neither have returns for the period March through June in 1976 and 1977, and for February 1978 through June 1978. Next, for Austria we have no monthly returns available from October 1979 through December 1979.

[24]We also take the definition of the average yield into account. Here, the monthly average for Germany until 1986 is based on the yield on the four weekly bank-return dates in each month, and the last day of the preceding month. The weekly bank-return dates are the 7th, 15th and 23rd and the last day of a month. If these are not a trading day, it is the last business day before. From 1986, the monthly average is based on all daily observations.

end-of-month government bond yield. Obviously, we use government bonds with a maturity that comes closest to the maturity of corporate bonds.

With data for the United States we show the beneficial effect of adding the difference between end-of-month and monthly average government bond yield to the average corporate bond yield. For the period 1973–1986 we can calculate a corporate bond index for the United States based on OECD corporate bond yields as the OECD Financial Statistics books contain corporate bond yields for the United States during this period.[25] Table A4 shows that a corporate bond index using average monthly bond yield has a correlation of 0.58 with the Bloomberg U.S. Corporate Investment Grade Index. This increases to 0.85 when we use the end-of-month adjustment in our yields. The compounded return and the average monthly return of the adjusted OECD corporate bond index are similar to those for Bloomberg U.S. Corporate Investment Grade Index. The average absolute monthly return difference between these two indices is 107 basis points, while the median is 76 basis points. That falls well below the standard deviation of monthly returns of 2.84% for the Bloomberg U.S. Corporate Investment Grade Index. Moreover, the Ibbotson SBBI Long-term Corporate Bond Index, which is the Citigroup Long-Term High-Grade Corporate Bond Index (formerly Salomon Brothers) for this sample period, just shows a slightly better match with the Bloomberg U.S. Corporate Investment Grade Index with a correlation of 0.89. The absolute differences for the Ibbotson SBBI Long-term Corporate Bond Index are smaller than for the index based on end-of-month adjusted OECD yields, but the compounded and median monthly returns are further away. In short, the analysis above suggests that the end-of-month adjustment for bond yields is a valuable and results in a representative corporate bond index.

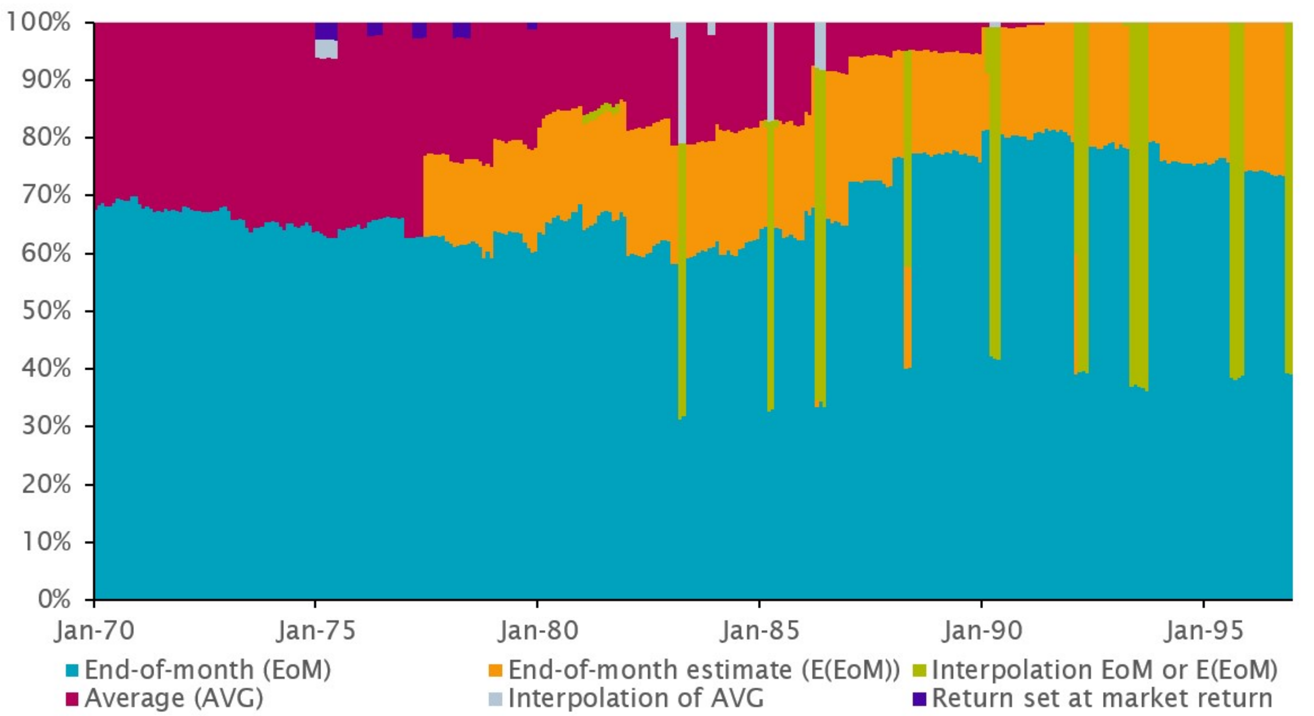
Figure A2 shows the different bond yield definitions underlying our corporate bond index. It shows that around two third of the index is based on end-of-month bond yields at the start of the sample, while the other part is based on average yields during that month or date such as the last Friday of a month. From July 1977, around 80% of the index is based on end-of month bond yields, or estimated end-of-month bond yields. From April 1986, around 90% of the index is based on end-of month bond yields, or estimated end-of-month bond yields. Afterwards, this weight slowly approaches 100%.

[25] We suppose a fixed maturity of 15 in our calculations as the OECD indicates it concerns long-term corporate bonds. The Bloomberg U.S. Corporate Bond Index starts in 1973 with a maturity of 20 and has a maturity of 15 at the end of 1986. As FRED data service provides 10- and 20-year constant maturity daily government bond yields, we use the average adjustment implied by both series to arrive at an estimate for the end-of-month corporate bond yields.

Table A4. Statistical characteristics for U.S. corporate bond indices (US$, monthly data 1973–1986)

	OECD based	OECD based with end of month adjustment	Ibbotson SBBI Long-term Corporate Bond Index	Bloomberg U.S. Corporate Investment Grade Index
Compounded return (%, annual)	9.54	9.43	9.23	9.47
Average return (%)	0.78	0.78	0.79	0.80
Median return (%)	0.61	0.68	0.61	0.72
Standard deviation	2.11	2.43	3.19	2.84
Minimum (%)	-6.97	-7.20	-8.90	-8.09
Maximum (%)	8.40	7.85	13.77	12.89
Correlation with BB U.S. Corp. Bond Index	0.58	0.85	0.89	1.00
Correlation with SBBI Long-term Corp. Bond Index	0.55	0.81	1.00	0.89
Average absolute difference with BB Index	1.76	1.07	0.70	
Median absolute difference with BB Index	1.40	0.76	0.40	

Figure A2. Corperate bonds bond yield data (1970–1996)



As most of the corporate bond index returns are based on end-of-month yields or estimated end-of-month yields, the monthly returns of the calculated global corporate bond index are likely to be a good estimate.[26]

[26] In a separate analysis (not included) it also appeared that a government bond index based on average yields for non-U.S. countries and end-of-month yields for the United States, comes very close to an index based solely on end-of-month yields, with a correlation of 0.97. In that analysis, we used the five countries that have both average and end-of-month yields available from 1979 to 1990.

B Changes relative to prior studies

We describe the differences in sources or methodology relative to the market values and returns described in Doeswijk et al. (2014) and Doeswijk et al. (2020). Despite the minor impact of each of the changes on the final results, they contribute to the accuracy of the composition and returns of the global market portfolio.

B.1 Cryptocurrencies

The first and most important change is the inclusion of crypto currencies as a separate asset class. Crypto currencies do not generate dividends or interest income, and they lack history and stability to regard them as a store of value. Further, particularly for (mandates of) institutional investors, investability has been constrained as there has been almost no regulatory framework, while exchanges and platforms bear a risk of a shut down due to hacks, and access is gone in case of loss of a personal key. However, market participants invest in crypto currencies. The market capitalization has surpassed 1 trillion U.S. dollars in January 2021, while the arrival of bitcoin futures in December 2017 at traditional exchanges has significantly improved investability. Therefore, we include crypto currencies as eleventh asset class that make up the global invested market portfolio. We categorize crypto currencies in the asset category commodities broad.

We use market capitalization data from www.coinmarketcap.com (CMC). We include crypto currencies from 2015, the first full calendar year with data availability for a cryptocurrency return index.[27] For returns we use the CMC 200 index available from the end of 2018. Before we use the CRIX, see Trimborn and Härdle (2018). Obviously, all returns are gross of losses due to hacks or lost access to crypto currency exchanges or crypto wallets.

B.2 Real Estate

The second change concerns the calculation of the market capitalization of real estate. For the period 1984–1998 we now backfill the market capitalization with an adjusted data series of the market capitalization of the GPR General World Index. Before 1999, the U.S. are underrepresented

[27] Due to lost access codes, we overestimate the market capitalization. To illustrate, results of Jahanshahloo et al. (2024) suggest 5% to 10% of bitcoins are lost.

in the GPR General World Index.[28] Hereby, we would underestimate the market capitalization of real estate before 1999. The adjustment follows the same methodology as the adjustment for global real estate returns in Doeswijk et al. (2020). Doeswijk et al. (2014) indicate that it is possible that they underestimate the weight of real estate. With this adjustment we arrive at an estimated weight for real estate in the global market portfolio of 3.0% at the end of 1984 instead of 2.2%. This comes closer to the estimated weight at that same point in time of commercial real estate of 4.3% in the U.S. wealth portfolio of Ibbotson et al. (1985).

B.3 High-Yield Bonds

The third change concerns the market capitalization of high-yield bonds from the end of 1997 to 2001. Doeswijk et al. (2020) relate it to a dynamic percentage of the Bloomberg Global Treasury Index. In this paper, we use relative changes in the market capitalization of the ICE BofAML Global High-Yield Index to backfill the market capitalization of the Bloomberg Global High-Yield Corporate Index. Before 1997, we follow the same methodology as Doeswijk et al. (2020).

B.4 Government Bonds

The fourth change concerns government bonds. For the market capitalization in the period 2001–2005, Doeswijk et al. (2020) use the Bloomberg Multiverse Government Index from 2005 on. Here, we use that index from 2001 instead of backfilling using relative changes in the Bloomberg Global Treasury Bond Index.[29] For returns, Doeswijk et al. (2020) use Ibbotson et al. (1985) data before 1985. Here, we use the return index for government bonds that we describe in Appendix A for the period before 1985 as it uses actual maturities instead of estimated maturities. It also has proven to be a very good estimate for the FTSE WGBI that starts in 1985.

[28] The GPR General World Index might be a good reflection of investment opportunities in U.S.-listed real estate during that period. However, our focus is on invested real estate by financial investors, both listed and unlisted. Regulatory changes in 1993 boosted the presence of U.S. REITs. After a few years, the regulatory changes led to a significant increase in the U.S. weight in the GPR General World Index, thereby affecting backfilling.

[29] Changes in the market capitalization of these two indices are similar as the Bloomberg Global Treasury Bond Index has a weight of 81% to 84% in the Bloomberg Capital Multiverse Government Index during these years. Therefore, this only has a marginal impact on the composition of the global market portfolio. In Doeswijk et al. (2014), authors were not aware of data availability of the Bloomberg Capital Multiverse Government Index before 2005. Like Doeswijk et al. (2020), we use free float corrected market capitalizations since the end of 2009.

B.5 Corporate Bonds

The fifth change relates to the maturities of corporate bonds. Doeswijk et al. (2020) used and extended the maturity estimates of Ibbotson et al. (1985) for the return calculations in the first part of their sample period. These are documented in more detail in Ibbotson et al. (1982). That last study mentions the OECD Financial Statistics as a source for the maturities of non-U.S. countries. However, after a closer inspection of these OECD books it appears that the description does not always match the maturities as documented in Ibbotson et al. (1982). In such cases, we use a maturity that matches the description in OECD Financial Statistics. Table B1 shows the changes we made in comparison to Ibbotson et al. (1985).[30]

Table B1. Maturity differences for investment-grade corporate bonds

Country	Ibbotson, Siegel and Love (1985)	This study
Germany	4	5.5 until 1977
	5	from 1977
Italy	13.5	13.5 until 1975
	6	from 1976
	5	from 1978
Netherlands	1976: 5	1976: 6.5
	1977: 4.5	1977: 6.25
	1978: 4	1978: 6.25
	1979: 3	1979: 6

Finally, we made one correction to the market value of investment-grade credits and government bonds. A reproduction of market capitalization data, for the period 2009–2017, showed an overestimation of the weights in the global market portfolio of these two asset classes by on average 0.9% and 1.1%, respectively, due to an incorrect processing of their free float adjustments. The reduction of their weights in the global market portfolio are proportionally allocated to the other ten asset classes. The impact of this correction on the returns of the global market portfolio is small. During the period 2010–2016 we underestimated the annual return of the global market portfolio on average by 5 basis points. The average absolute difference is 13 basis points. In 2017 the return of the global market portfolio is 28 basis points above the global market portfolio documented in Doeswijk et al. (2020). But that follows from a 2,764% rise in the crypto currency

[30]In addition, we changed the maturity for Spain from 17.5 to 6 from 1989, and for Japan from 4.5 to 12 from March 1992.

index, driving a return of commodities broad of 39.9%. Cryptocurrencies were not included in Doeswijk et al. (2020).

C Definitions and sources of risk-free interest rates

Table C1. Definitions and sources of risk-free interest rates

Country	Definition and source
Australia	
1970–2022	3-month Treasury notes at issue - Global Financial Data
Canada	
1970–2022	3-month Treasury bills, auction yields through 1989 and secondary market yields from 1990 on - Global Financial Data
Eurozone	
1970–May 1971	60 to 90 days yield on German Treasury bills of the Federal Government and Federal Railways, money market paper included in the Deutsche Bundesbank's market regulating arrangements. To this series we add a constant 2.15%, that is the average difference over the period June 1971 to December 1972 with the subsequent series that we use - Monthly reports of the German Bundesbank
June 1971–1978	6-month German yield on discountable Treasury bonds of Federal Government, money market paper not included in the Deutsche Bundesbank's market regulating arrangements. Since June 3, 1971 discountable Treasury bonds not included in money market arrangements are sold at different (higher) rates - Monthly reports of the German Bundesbank
1979–2022	Bundesbank estimate (method by Svensson) of the interest rate on listed Federal securities with a residual maturity of 6 months - Bundesbank website
Japan	
1970–2022	Treasury bills, varying from 60 days to 6 months during sample period - Global Financial Data
New Zealand	
1970–2022	6-month term deposit rate - Reserve Bank of New Zealand

Country	Definition and source
Norway	
1970–1985	3-month money market rates - Norges Bank
1986–2002	3-month Treasury bills secondary market - Eitrheim and Klovland (2007)
2003–2022	3-month Treasury bills secondary market - Norges Bank
Sweden	
1970–1981	3-month rate on Treasury discount notes - IMF International Financial Statistics
1982–2022	3-month rate on Treasury discount notes - OECD through Federal Reserve Bank of St. Louis
Switzerland	
1970–2022	3 month time deposit rates at big banks in Zurich - Global Financial Data
U.K.	
1970–2022	3-month Treasury bill rate of discount at tenders - Office of National Statistics, from Global Financial Data
U.S.	
1970–2022	3-month Treasury Bills secondary market - Federal Reserve Bank of St. Louis

D Results for real and nominal returns

Table D1. Return characteristics of the invested global market portfolio (1970–2022)
Compounded return, average return, volatility, median, minimum, maximum, maximum DD at monthly data and maximum DD at annual data in percentages, DD > x% are counts, DD duration, and the Sharpe and MAR ratio don't have units. The MAR ratio divides the compounded average annual return by the maximum DD. DD is the abbreviation for drawdown.

	AUD	CAD	EUR	JPY	NZD	NOK	SEK	CHF	GBP	USD	AVG	DISP
Panel A. Real monthly returns												
Comp return	0.32	0.38	0.31	0.30	0.28	0.33	0.40	0.23	0.33	0.33	0.32	0.17
Avg return	0.37	0.41	0.36	0.36	0.33	0.38	0.45	0.29	0.38	0.37	0.37	0.16
Volatility	3.08	2.56	3.04	3.44	3.25	2.88	2.98	3.40	3.02	2.90	3.05	0.88
Median	0.33	0.42	0.52	0.71	0.23	0.41	0.50	0.69	0.50	0.52	0.48	0.48
Minimum	-10.0	-9.1	-13.9	-20.0	-9.8	-11.0	-11.8	-14.5	-13.5	-13.6	-12.7	10.9
Maximum	20.9	9.5	13.1	9.1	24.9	10.3	23.1	11.1	12.2	8.8	14.3	16.0
'Sharpe'ratio	0.42	0.56	0.41	0.36	0.35	0.45	0.52	0.30	0.43	0.45	0.42	0.26
Max DD mth	49.3	38.9	47.9	56.3	45.3	47.8	43.2	56.7	42.8	38.0	46.6	18.7
Max DD ann	42.5	36.0	47.9	51.6	42.3	47.8	43.2	55.8	40.6	35.2	44.3	20.5
MAR ratio	0.080	0.119	0.080	0.065	0.075	0.085	0.114	0.050	0.095	0.107	0.087	0.069
DD > 10%	6	8	11	8	7	9	10	12	11	11	9	6
DD > 20%	3	5	5	4	3	3	3	7	4	4	4	4
DD > 30%	2	1	2	2	2	2	1	4	2	2	2	3
DD > 40%	1	0	1	2	2	1	1	1	1	0	1	2
DD > 50%	0	0	0	1	0	0	0	1	0	0	0	1
Max DD dur.	176	81	163	192	204	156	117	164	135	144	153	123
Panel B. Nominal monhtly returns												
Comp return	0.74	0.69	0.55	0.50	0.75	0.71	0.77	0.41	0.77	0.66	0.65	0.35
Avg return	0.78	0.73	0.59	0.56	0.80	0.75	0.81	0.47	0.81	0.70	0.70	0.34
Volatility	3.09	2.56	3.04	3.41	3.28	2.88	2.98	3.39	3.01	2.90	3.05	0.85
Median	0.71	0.66	0.79	0.86	0.73	0.82	0.90	0.81	0.85	0.81	0.79	0.24
Minimum	-9.1	-8.3	-13.8	-19.9	-9.5	-10.5	-11.5	-14.4	-13.3	-13.6	-12.4	11.6
Maximum	22.3	10.3	13.0	9.1	25.8	11.1	24.0	11.1	12.4	9.4	14.9	16.7
'Sharpe'ratio	0.88	0.98	0.68	0.57	0.84	0.90	0.94	0.48	0.93	0.84	0.80	0.50
Max DD mth	36.5	28.2	40.5	46.3	37.1	37.9	31.9	46.7	26.5	34.8	36.7	20.2
Max DD ann	24.5	21.3	40.5	38.6	28.4	37.9	31.9	46.7	22.1	24.3	31.6	25.5
MAR ratio	0.252	0.306	0.167	0.133	0.252	0.233	0.302	0.109	0.362	0.235	0.235	0.253
DD > 10%	9	8	10	10	8	8	8	12	10	10	9	4
DD > 20%	2	2	4	4	2	3	3	5	3	4	3	3
DD > 30%	1	0	2	1	2	2	1	3	0	1	1	3
DD > 40%	0	0	1	1	0	0	0	1	0	0	0	1
DD > 50%	0	0	0	0	0	0	0	0	0	0	0	0
Max DD dur.	68	69	91	75	153	73	53	115	58	44	80	109