The Golden CAPM*

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Abstract

When asset returns are measured in ounces of gold rather than U.S. dollars, the Capital Asset Pricing Model (CAPM) holds. Indeed, regressing asset returns onto market betas yields an intercept that is economically small and statistically indistinguishable from zero. Moreover, the slope is remarkably close to the average market return and statistically significant. That is, the golden CAPM successfully explains the cross-section of expected returns. We show that denominating returns in ounces of gold improves the explanatory power of multi-factor models such as the Fama-French 3-, 5-, and 6-factor models, and the Carhart 4-factor model. Yet, across all model-test asset combinations, none outperforms the simple golden CAPM applied to beta-sorted portfolios.

Keywords: Capital Asset Pricing Model, Asset Pricing Tests, Gold

JEL Classification: D53, G11, G12

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1 Introduction

An extensive body of finance research focuses on understanding how investors value risky investments and determine the appropriate discount rates for uncertain cash flows. The most prominent and influential theoretical framework in this field is the capital asset pricing model (CAPM) introduced by Sharpe (1964), Lintner (1965), Mossin (1966), and Treynor (1961), which marked the birth of asset pricing theory and earned William F. Sharpe the 1990 Nobel Prize in Economics. The appeal of the CAPM lies in its simple and intuitive economic logic. It offers a single-factor model where an asset's expected return is linearly related to its systematic risk, measured by market beta. The CAPM continues to be taught in business schools around the world and is widely used by practitioners for making investment decisions (Barber, Huang, and Odean, 2016; Berk and van Binsbergen, 2016) and for computing the cost of capital (Graham and Harvey, 2001).

Yet, despite its popularity in practice, empirical evidence finds little support for the CAPM. The consensus in asset pricing research is that market beta alone cannot explain the cross-section of expected returns. Studies have documented other variables such as firm size (Banz, 1981; Fama and French, 1992), book-to-market ratios (Rosenberg, Reid, and Lanstein, 1985; Fama and French, 1992), and momentum (Jegadeesh and Titman, 1993), among others, capture variation in returns unexplained by beta. Fama and French (1992) further confirm that the security market line (SML), which plots the relationship between average asset returns and beta, is flatter than predicted by the CAPM. Kothari, Shanken, and Sloan (1995) attempts to resurrect the validity of the CAPM, showing that the risk-return relationship is strong when measured at annual intervals. Tinic and West (1984) document that the positive relationship between beta and average returns holds only in January, while Cohen, Polk, and Vuolteenaho (2005) show that the CAPM cannot be rejected during periods of low inflation. In a more recent paper, Hasler and Martineau (2023) show that the CAPM performs fairly well during periods of low volatility, low uncertainty, high attention, and high (positive) investor sentiment.

In light of these findings, this paper argues that the empirical failure of the CAPM stems from the choice of the monetary unit rather than from a limitation of the theoretical framework. We do not claim that alternative theories are wrong. Instead, we simply show that if asset returns are expressed in ounces of gold, as they were when the Sharpe-Lintner CAPM was introduced,[1] the predictions of the model find empirical support. Indeed, regressing asset returns on their market betas yields an intercept that is economically small and statis-

[1] The authors do not explicitly state that returns should be measured in ounces of gold. However, at the time, the U.S. dollar was pegged to gold at a fixed rate, so dollar-denominated and gold-denominated returns were identical.

tically indistinguishable from zero. The estimated slope is economically large, statistically significant, and closely aligned with the average market return. That is, the CAPM explains the cross-section of expected returns.

Empirical tests are performed on beta-sorted portfolios using Fama-MacBeth and pooled regressions (Fama and MacBeth, 1973; Savor and Wilson, 2014; Martin and Wagner, 2019; Hasler and Martineau, 2023). We first estimate market betas for all stocks using rolling windows of 36 past monthly gold-denominated returns from 1926 to 2024. We then sort stocks into one of the 20 beta-sorted portfolios and compute their respective value-weighted gold-denominated returns (hereafter referred to as *golden returns*). When returns are measured in ounces of gold, a strong positive relationship emerges between average returns and beta. A one-unit increase in beta is associated with a 57-basis-point increase in average monthly returns, with a t-statistic exceeding five. In addition, the slope is both economically and statistically indistinguishable from the market's average monthly return of 58 basis points (bps). Regressions also show that the level of average golden returns is almost entirely explained by beta. Indeed, the estimated intercept is economically negligible (around 3 bps) and statistically insignificant. These results are robust and do not depend on the portfolio construction choice. The strong positive risk-return relationship holds regardless of whether betas are estimated over 24-, 36-, 48-, or 60-month rolling windows; whether assets are sorted into 10, 20, or 50 portfolios; or whether these portfolios are rebalanced monthly or annually (Black, Jensen, Scholes, et al., 1972; Fama and French, 2004). Importantly, the relationship disappears when returns are measured in dollars, resulting in a small, insignificant slope and a large, significant intercept.

The relationship between expected golden returns and beta also holds when considering the 25 Fama-French size- and book-to-market-sorted portfolios and the ten industry-sorted portfolios in the set of test assets. Indeed, pooling these 35 portfolios together with the 20 beta-sorted portfolios yields a statistically insignificant and economically negligible intercept of 1 bp per month, and a strongly statistically significant slope of 64 bps. Using dollar returns, we confirm existing evidence that betas do not explain the level of asset returns. The intercept is economically large (around 40 bps) and statistically significant, whereas the slope is only 34 bps, substantially lower than the average market return. These results suggest that the failure of the CAPM can be attributed to the choice of denominating returns in a fiat currency rather than in gold, the monetary metal that has served as a global currency for thousands of years.

Motivated by these findings, we extend our analysis to examine whether conditional betas can explain the cross-section of golden returns. We show that the results are sensitive to the choice of the beta estimation window. When betas are estimated over windows of up to 60 months, the intercept ranges from about −15 to 20 bps, whereas the slope ranges from about 40 to 70 bps. When the estimation window is 120 months, the intercept becomes substantially smaller (around 1 bp) and the slope particularly well aligned with the average market return of 58 bps. These results suggest that betas estimated over longer horizons are more reliable measures of systematic risk, and that true betas might actually be constant. When returns are denominated in dollars, intercepts are economically large (around 40 bps) and slopes are only half the average market return, irrespective of the beta estimation window.

The empirical failure of the CAPM gave birth to alternative multi-factor models designed to better explain the cross-section of expected returns. In their seminal paper, Fama and French (1993) propose a three-factor model that successfully captures differences in returns across assets. Since then, many models have been shown to outperform the CAPM in explaining return patterns. We therefore compare the ability of several prominent asset pricing models to explain asset returns, including the Fama and French (1993) three-factor model, the three-factor model augmented with the momentum factor of Carhart (1997), the Fama and French (2015) five-factor model, and the Fama and French (2018) six-factor model. The tests are performed on three sets of portfolios: beta-sorted, size- and book-to-market-sorted, and industry-sorted portfolios. The results show that golden returns are better explained than their dollar counterparts, for all factor models and sorted portfolios considered. As argued by Lewellen, Nagel, and Shanken (2010), asset pricing tests are sensitive to the choice of test assets. Across all model-portfolio combinations tested, the golden CAPM applied to the 20 beta-sorted portfolios exhibits the highest performance. It is also the best performing model in explaining the returns of the ten industry-sorted portfolios.

A possible explanation for our results lies in the history of gold as a monetary unit. For over five thousand years, gold has served as a medium of exchange and a store of value. Jastram (2009) and Erb and Harvey (2013) document that gold has maintained its purchasing power for more than two thousand years, a phenomenon they refer to as the *golden constant*. The classical gold standard (1870s–1914) established fixed exchange rates between national currencies and specified gold quantities. The shift towards a fiat currency system began in the early 20th century, due to World War I and the Great Depression of 1929, and accelerated after the United States abandoned the Bretton Woods system in 1971. This marked the end of the dollar–gold convertibility. The creation of fiat currencies was driven by the desire for greater flexibility in monetary policy, enabling governments and central banks to respond more promptly to economic crises and manage economic growth. This shift has not been without critics. For instance, Von Mises (1953) argues that money must originate from a commodity with pre-existing value. Gold satisfies this requirement through its durability, divisibility, portability, and limited supply. Former Federal Reserve Chairman Alan Greenspan confirms this view in an interview with the *Gold Investor Magazine* in 2017. He mentions: *"I view gold as the primary global currency [...] No one refuses gold as payment to discharge an obligation [...] Credit instruments and fiat currency depend on the credit worthiness of a counterparty. Gold is one of the only currencies that has an intrinsic value. It has always been that way. No one questions its value"* Our results that the CAPM holds when returns are denominated in ounces of gold are consistent with this view. Gold measures the true intrinsic value of assets, free from the distortions introduced by monetary policies. We do not advocate for a return to the gold standard. Rather, our findings simply show that golden returns restore the fundamental risk-return relationship predicted by asset pricing theory.

Our paper is closely related to the literature that attempts to resurrect the CAPM by expanding the market portfolio. Roll (1977) provides the seminal critique that the market portfolio is inherently unobservable, as true wealth includes human capital and other non-traded assets. In response to this critique, several studies have proposed an alternative market proxy. Stambaugh (1982) extends the market portfolio beyond the traditional value-weighted returns of all U.S. common stocks to include returns for bonds, real estates, and other consumer durables. Even when stocks represent a minor part of the market portfolio, the CAPM's performance in explaining the cross-section of returns does not improve. Jagannathan and Wang (1996) include human capital in their measure of the market portfolio. This significantly improves the CAPM's ability to explain the cross-section of returns. Fama and French (1998) extend the market portfolio by including international stocks. However, the authors document that the international CAPM fails to explain the value premium in international stock returns. Adrian, Etula, and Muir (2014) argue that measuring market risk using the wealth of financial intermediaries yields a substantially better proxy than traditional stock market indices.

Another strand of the literature attributes the CAPM's empirical failure to financing constraints or informational frictions. Black (1972, 1993) argues that unrestricted lending and borrowing at the risk-free rate is an unrealistic assumption. When this assumption is violated due to investors' limited borrowing capacity, the demand for high-beta assets is high and that of low-beta assets is low. Consequently, the slope of the SML is flatter than predicted by the CAPM. Frazzini and Pedersen (2014) propose a betting against beta (BaB) strategy that exploits the flat SML by going long low-beta assets and short high-beta assets. Andrei, Cujean, and Wilson (2023) show that, although the CAPM is the correct model, an econometrician incorrectly rejects it because of its informational disadvantage. Andrei, Cujean, and Fournier (2019) argue that the existence of anomalies is not necessarily evidence against the CAPM.

Our paper is also related to the literature studying the risk-return relationship over different time periods. Tinic and West (1984) show that the CAPM holds in January but fails during the remaining eleven months of the year. Cohen et al. (2005) document that average asset returns increase with beta during months of low inflations. Savor and Wilson (2014) further show that beta explains average returns on days of macroeconomics announcements. Hong and Sraer (2016) document that the SML is markedly upward-sloping when disagreement among investors is low. Jylhä (2018) shows that when margin requirements are low and leverage constrains are slack, the SML exhibits a positive slope consistent with the CAPM's prediction. Hendershott, Livdan, and Rösch (2020) show that the SML is upward-sloping overnight when the stock market is closed, but downward-sloping during regular trading hours. Ben-Rephael, Carlin, Da, and Israelsen (2020) further show that average asset returns increase with beta when investor attention is high. Hasler and Martineau (2023) document that the CAPM performs well during periods of low volatility, low uncertainty, high attention, and high investor sentiment. Our paper contributes to this literature by showing that the CAPM's validity is not conditional on specific economic states but rather on the choice of the monetary unit. If returns are measured in ounces of gold, the model holds unconditionally.

The remainder of the paper is organized as follows. Section 2 provides the theoretical motivation. Section 3 discusses the data and our empirical results. Section 4 provides robustness tests, and Section 5 concludes.

2 Theoretical Motivation

This section briefly discusses the CAPM and golden CAPM.

2.1 The CAPM

The Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), Mossin (1966), and Treynor (1961) is an equilibrium extension of the optimal portfolio choice problem developed by Markowitz (1952). The CAPM's prediction is that the risk premium on any stock is a linear function of its beta, which is defined as the covariance between the stock return and the market return over the variance of the market return. Specifically, the CAPM is written as

$$\mathbb{E}[R_i - R_f] = \beta_i \times \mathbb{E}[R_m - R_f], \tag{1}$$

where R_i is the return of stock i, R_f is the risk-free rate, R_m is the market return, and $\beta_i = \frac{Cov(R_i,R_m)}{Var(R_m)}$ is the beta of asset i.

Black et al. (1972) document that average returns do increase with beta, but less than predicted by the model. Fama and MacBeth (1973) further show that cross-sectional regressions produce slopes and intercepts that are respectively below and above those predicted by the CAPM. This flat security market line (SML) leads to the conclusion that the CAPM consistently understates the risk premiums of low-beta assets and overstates those of high-beta assets. Subsequent work extends these findings. Basu (1977) and Banz (1981) provide evidence that stocks with low price-earnings (P/E) ratios and small market capitalizations earn higher returns than those predicted by their betas. Rosenberg et al. (1985) and Fama and French (1992) show that book-to-market (B/M) ratios further capture variation in average returns missed by beta alone. To address this challenge, researchers have explored a large number of systematic or common risk factors, resulting in what Cochrane (2011) describes as a *factor zoo*. Hou, Xue, and Zhang (2020) show that between 64% and 85% of the 447 anomalies identified in the literature are in fact statistically insignificant. Harvey, Liu, and Zhu (2016) argue that most anomalies in the existing literature suffer from multiple testing problems, and that many reported anomalies are likely false positives due to data mining. Rather than examining individual factors in isolation, Kozak, Nagel, and Santosh (2020) use machine learning techniques and find that only a small subset of factors are genuinely useful for explaining returns. In a more recent paper, Harvey and Liu (2021) and Hasler and Martineau (2023) show that the market is a particularly important determinant of expected asset returns, and the next generation of factors are of second-order importance. All these results raise a simple question: *"Does the CAPM really fail?"*

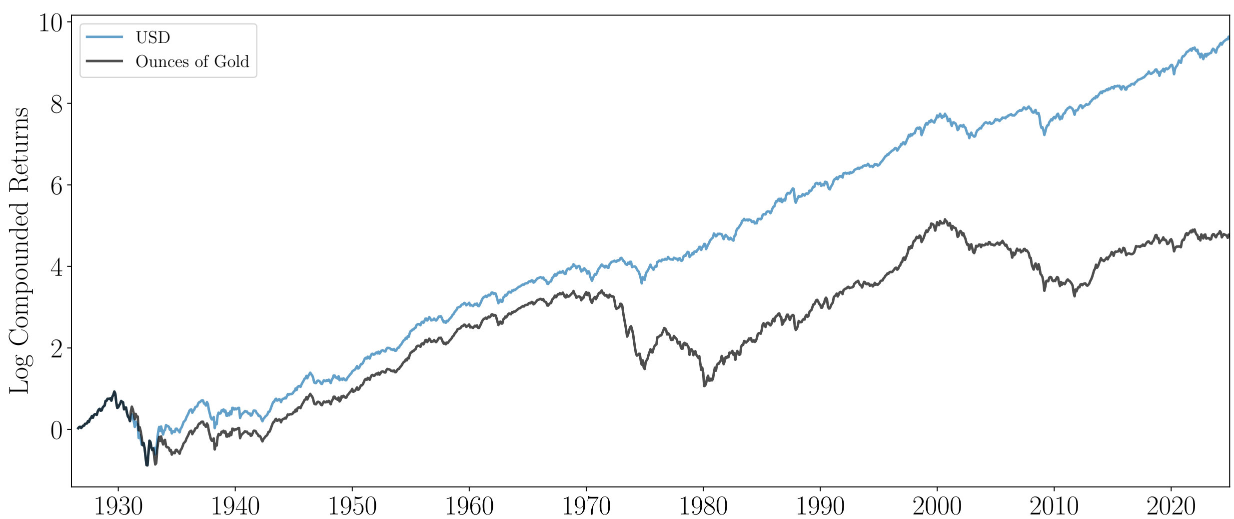
2.2 The Golden CAPM

Fama and French (2004) note that empirical research starts challenging the validity of the CAPM during the 1970s. Interestingly, this period coincides with the collapse of the Bretton Woods system[2] in 1971, when President Richard Nixon announced the suspension of the dollar-to-gold convertibility. Figure 1 plots the stock market growth denominated in ounces of gold (black line) and U.S. dollars (blue line). It provides direct evidence that until 1971 the market behaves similarly when measured in either monetary unit.[3] However, after 1971 the market grows more rapidly when measured in dollars than when measured in ounces of

[2]Under this system, the U.S. committed to convert dollars to ounces of gold at a fixed rate of \$35 per ounce. Other countries tied their currencies to the dollar at a fixed rate allowing currencies to fluctuate within ±1% of their par value.

[3]In 1934 the U.S. dollar was devalued from \$20.67 to \$35 per ounce. This rate was then maintained through the Bretton Woods period (1944-1971).

Figure 1: Stock Market Growth in Ounces of Gold versus U.S. dollars
This figure plots the log stock market compounded return in U.S. dollars (blue line) and in ounces of gold (black line) for the period July 1926 to December 2024. The market compounded return is computed as either $\prod_{t=1}^{T}(1+R_{m,t})$, where $R_{m,t}$ denotes the market monthly return in dollars, or $\prod_{t=1}^{T}\left(1+R^{\mathbf{g}}_{m,t}\right)$, where $R^{\mathbf{g}}_{m,t}$ is the market monthly return in ounces of gold. The market is the CRSP stock market index obtained from Kenneth French's website. The gold price is obtained from the Gold World Council.



gold, highlighting a clear divergence between the two monetary units.

Our paper aims to reexamine the CAPM's core equation in the context of the aforementioned historical shift away from the gold standard. We therefore consider gold-denominated asset returns instead of the traditional dollar-denominated returns. More specifically, assets and market returns satisfy[4]

$$R^{\mathbf{g}}_i = \frac{1+R_i}{1+R_{gold}} - 1,$$
$$R^{\mathbf{g}}_m = \frac{1+R_m}{1+R_{gold}} - 1, \quad (2)$$

where R_i and R_m are respectively the dollar-denominated returns of asset i and the market m, and R_{gold} is the dollar-denominated return of one ounce of gold. Thus, $R^{\mathbf{g}}_i$ and $R^{\mathbf{g}}_m$ are the returns of respectively asset i and the market m expressed in ounces of gold (henceforth, *golden returns*). The golden CAPM is written

$$\mathbb{E}[R^{\mathbf{g}}_i] = \beta^{\mathbf{g}}_i \times \mathbb{E}[R^{\mathbf{g}}_m], \quad (3)$$

[4]See Appendix C.

where $\beta_i^{\mathbf{g}} = \frac{\text{Cov}(R_i^{\mathbf{g}}, R_m^{\mathbf{g}})}{\text{Var}(R_m^{\mathbf{g}})}$ is the market beta of asset i obtained using golden returns (henceforth, *golden beta*). Note that the traditional CAPM (1) uses excess returns, whereas the golden CAPM (3) uses regular returns. The reason is that in the traditional CAPM the risk-free rate is the return on holdings of cash, or in other words, on holdings of the currency. Indeed, holding one dollar today translates into holding $(1+R_f)$ dollars next period. In the golden CAPM framework, holding the currency means holding ounces of gold. Because holding one ounce of gold today translates into holding one ounce of gold next period, the return on holdings of the currency is zero in the golden CAPM.

To understand the difference between traditional beta and golden beta, let us compute the golden beta of asset i using log returns $r \equiv log(1+R)$:[5]

$$\beta_i^{\mathbf{g}} = \frac{Var(r_m)}{Var(r_m) + Var(r_{gold}) - 2Cov(r_m, r_{gold})}\beta_i - \frac{Var(r_{gold})}{Var(r_m) + Var(r_{gold}) - 2Cov(r_m, r_{gold})}\beta_i^{gold}$$
$$+ \frac{Var(r_{gold}) - Cov(r_{gold}, r_m)}{Var(r_m) + Var(r_{gold}) - 2Cov(r_m, r_{gold})},$$

where $\beta_i^{gold} \equiv \frac{Cov(r_i, r_{gold})}{Var(r_{gold})}$ is the exposure of the dollar-denominated return of asset i to the dollar-denominated return of the ounce of gold.

If the correlation between the dollar-denominated return of the market and the dollar-denominated return of the ounce of gold is close to zero ($Cov(r_m, r_{gold}) \approx 0$), the golden beta of asset i simplifies to

$$\begin{aligned} \beta_i^{\mathbf{g}} \approx & \underbrace{\frac{Var(r_m)}{Var(r_m) + Var(r_{gold})}}_{\equiv \omega}\beta_i - \underbrace{\frac{Var(r_{gold})}{Var(r_m) + Var(r_{gold})}}_{\equiv 1-\omega}\beta_i^{gold} + \underbrace{\frac{Var(r_{gold})}{Var(r_m) + Var(r_{gold})}}_{\equiv 1-\omega} \\ = & \omega\beta_i + (1-\omega)\left(1 - \beta_i^{gold}\right). \end{aligned} \tag{4}$$

Equation (4) shows that the golden beta $\beta_i^{\mathbf{g}}$ is a linear combination of the traditional market beta β_i and the gold beta β_i^{gold}, defined as the exposure of asset i dollar-return to the ounce of gold dollar-return in a univariate linear regression. The definition of the weight ω shows that when the gold price is stable, which was the case prior to the 1970s, the golden beta is close to the traditional beta. As the volatility of gold increases relative to that of the market, the golden beta departs from the traditional beta and starts reflecting the asset return exposure to the gold return. Equation (4) together with the golden CAPM (3) imply that the expected return of an asset increases with the asset's exposure to the market, as in

[5] See Appendix C.

the traditional CAPM, and decreases with the asset's exposure to gold. The more exposed an asset is to gold, the better it hedges investors against changes in monetary policy, and therefore the lowest its expected return. Thus, although the golden CAPM (3) is a 1-factor model in the gold-denominated framework, it can be interpreted as a 2-factor model when expressed in the traditional dollar-denominated framework. The market and gold represent the two factors, and asset exposures to these two factors are estimated via two separate univariate linear regressions.

To gauge the accuracy of Equation (4) and the magnitude of the weight ω, we estimate the market return variance, gold return variance, and correlation between the market and gold returns using monthly data from 1926 to 2024 (full sample) and from 1971 to 2024 (post-Bretton Woods sample). The correlation between the market and gold returns is -0.0066 over the full sample and -0.036 over the post-Bretton Woods sample. Both correlations are close to zero, implying that Equation (4) is an accurate approximation. The estimated weight ω is 0.64 using the full sample and 0.46 using the post-Bretton Woods sample. These magnitudes highlight the importance of the gold beta β_i^{gold} in explaining expected asset returns. Indeed, because ω and $(1-\omega)$ are of similar magnitudes, the asset exposure to gold β_i^{gold} provides a nearly one-for-one counterbalance to the asset exposure to the market β_i. That is, assets that are highly exposed to the market and weakly exposed to gold are considered high risk, and therefore have high expected returns. Conversely, assets with low exposure to the market and high exposure to gold have low risk and low expected returns.

Modigliani and Cohn (1979) suggest that stock market investors suffer from *"money illusion"*. Cohen et al. (2005) further examine this phenomenon and find that the CAPM holds during normal times, but fails during periods of high inflations. Thorbecke (1997) shows that monetary policy changes have significant effects on equity valuations. By measuring returns in ounces of gold instead of dollars, our framework aims to control for the effects of money illusion and changes in monetary policy.

3 Empirical Methodology and Results

In this section, we describe the data and the empirical methodology. We show that the CAPM is not rejected by the data when tested with golden returns, whereas it is rejected when tested with dollar returns, consistent with existing findings. The unconditional CAPM stated in Equations (1) and (3) is tested on 20 beta-sorted portfolios, 25 size- and book-to-market-sorted portfolios, and ten industry-sorted portfolios. We then investigate the validity of the conditional CAPM by estimating portfolio betas over a trailing window, and compare its performance to that of the unconditional CAPM. We further perform model comparisons by examining the explanatory power of the CAPM, Fama-French three-factor model (Fama and French, 1993), Carhart four-factor model (Carhart, 1997), Fama-French five-factor model (Fama and French, 2015), and Fama-French six-factor model (Fama and French, 2018).

3.1 The Data

We obtain monthly gold prices in USD for the period from January 1833 to December 2024 from the World Gold Council and the World bank.[6] From Kenneth French's website,[7] we retrieve returns for the 25 size- and book-to-market-sorted portfolios, the ten industry-sorted portfolios, as well as the NYSE market equity breakpoints. From this same source, we also obtain the risk-free rate (Rf), defined as the one-month Treasury bill rate, the market excess return (Rm–Rf), the small-minus-big (SMB), high-minus-low (HML), robust-minus-weak (RMW), conservative-minus-aggressive (CMA), and momentum (MOM) factors (Fama and French, 1993, 2015; Carhart, 1997).

Our main tests examine the intercept and the slope of the security market line (SML) obtained by measuring asset returns in either ounces of gold or dollars. Following Black et al. (1972), Savor and Wilson (2014), Jylhä (2018), Hendershott et al. (2020), and Hasler and Martineau (2023) among others, we construct 20 monthly beta-sorted portfolios using U.S. common stocks (with share codes 10 and 11) traded on the NYSE, Amex, and Nasdaq over the period from Januray 1926 to December 2024. Dollar returns are converted into golden returns using Equation (2). The rolling betas of each stock are estimated using a trailing window of 36 past monthly returns.[8] At the beginning of each month, stocks are sorted into one of the 20 portfolios, where portfolio 1 contains low-beta assets and portfolio 20 contains high-beta assets. We use monthly value-weighted portfolio returns because wealth effects, transactions costs, and microstructure frictions make value-weighted returns more suitable than equal-weighted returns for asset pricing tests (Hou et al., 2020). The portfolio return series span the period from July 1927 to December 2024. Each portfolio p unconditional beta is estimated over the full sample using either golden returns, $\hat{\beta}_p^{\mathbf{g}}$, or dollar returns, $\hat{\beta}_p$.

3.2 Beta-Sorted Portfolios

Table 1 reports summary statistics for 20 beta-sorted portfolios constructed using golden returns in Panel A and dollar returns in Panel B. The last column (Mkt) reports the summary statistics for the market. The average monthly market return is 58 bps (6.96% annually) with

[6] https://datahub.io/core/gold-prices

[7] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[8] If for a given stock the availability of returns is less than 36 months, we require at least 12 months of returns to calculate the stock's monthly beta.

Table 1: Summary Statistics for 20 β-Sorted Portfolios

This table presents summary statistics for the 20 beta-sorted portfolios of all publicly listed common stocks from July 1927 to December 2024. Portfolios are rebalanced each month, with stocks sorted according to their prior beta, estimated using monthly returns over a three-year rolling window. The last column (Mkt) reports the summary statistics for the market portfolio. Panel A reports the portfolios unconditional golden beta ($\hat{\beta}^{\mathbf{g}}$). We further report portfolio average monthly golden returns ($\bar{R}^{\mathbf{g}}$) and their volatility, defined as the standard deviation of realized returns (std($R^{\mathbf{g}}$)). *Mkt. Cap.* is the average ratio of portfolio market capitalization divided by the total market capitalization of all stocks in the sample. $\bar{N}$ stocks is the average number of stocks in each portfolio. Panel B reports the summary statistics obtained using dollar returns. $\hat{\beta}^g - \hat{\beta}$, represents the difference between golden and traditional portfolio betas.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	Mkt
Panel A: Golden Returns																					
$\hat{\beta}^{\mathbf{g}}$	0.7332	0.7855	0.8018	0.8507	0.8635	0.9187	0.9351	0.9782	0.9975	1.0546	1.0823	1.1199	1.1435	1.2010	1.2173	1.2716	1.3431	1.3856	1.4594	1.5641	1.0000
$\bar{R}^{\mathbf{g}}$	0.0023	0.0037	0.0050	0.0048	0.0052	0.0067	0.0064	0.0071	0.0067	0.0066	0.0068	0.0072	0.0070	0.0073	0.0076	0.0077	0.0086	0.0085	0.0077	0.0079	0.0058
std ($R^{\mathbf{g}}$)	0.0628	0.0601	0.0587	0.0604	0.0610	0.0643	0.0648	0.0674	0.0685	0.0725	0.0741	0.0768	0.0784	0.0829	0.0845	0.0888	0.0948	0.1004	0.1071	0.1211	0.0653
Mkt. Cap.	0.0235	0.0434	0.0491	0.0620	0.0619	0.0646	0.0660	0.0681	0.0656	0.0644	0.0632	0.0593	0.0544	0.0504	0.0459	0.0413	0.0380	0.0285	0.0203	0.0124	1.0000
$\bar{N}$ stocks	146	146	147	147	147	147	147	147	147	147	147	147	147	147	147	147	147	147	147	147	3169
Panel B: Dollar Returns																					
$\hat{\beta}$	0.5638	0.6345	0.6656	0.7498	0.8169	0.8131	0.8962	0.9817	1.0111	1.1435	1.1705	1.1814	1.2199	1.3025	1.3888	1.4080	1.5420	1.6195	1.7635	1.9145	1.0000
$\bar{R}$	0.0062	0.0081	0.0086	0.0085	0.0096	0.0090	0.0106	0.0108	0.0097	0.0108	0.0103	0.0101	0.0107	0.0111	0.0102	0.0111	0.0119	0.0102	0.0113	0.0112	0.0092
std (R)	0.0462	0.0433	0.0428	0.0459	0.0486	0.0486	0.0522	0.0572	0.0577	0.0658	0.0639	0.0673	0.0696	0.0741	0.0790	0.0804	0.0890	0.0945	0.1043	0.1187	0.0533
Mkt. Cap.	0.0272	0.0523	0.0571	0.0634	0.0654	0.0669	0.0675	0.0665	0.0617	0.0612	0.0601	0.0564	0.0545	0.0485	0.0422	0.0393	0.0337	0.0258	0.0192	0.0128	1.0000
$\bar{N}$ stocks	146	147	147	147	147	147	147	147	147	147	147	147	147	147	147	147	147	147	147	147	3169
$\hat{\beta}^{\mathbf{g}} - \hat{\beta}$	0.1694	0.1510	0.1362	0.1009	0.0466	0.1056	0.0389	-0.0035	-0.0136	-0.0889	-0.0287	-0.0615	-0.0764	-0.1015	-0.1715	-0.1364	-0.1989	-0.2339	-0.3041	-0.3504	

golden returns and 92 bps (11.04% annually) with dollar returns. This confirms previous findings from Figure 1 that the market grows at a faster pace when returns are denominated in dollars rather than in ounces of gold. Monthly market return volatility is 6.53% (22.62% annually) with golden returns and 5.33% (16.46% annually) with dollar returns.

With golden returns (Panel A), the unconditional beta of the high-beta portfolio is about twice that of the low-beta portfolio. Moreover, there is a clear increasing relationship between average portfolio returns and beta. With dollar returns (Panel B), the dispersion in unconditional beta is much wider; the beta of the high-beta portfolio is nearly four times that of the low-beta portfolio. However, the relationship between average portfolio returns and beta is unclear. This provides preliminary evidence that the relationship between average returns and beta seems fairly strong when using golden returns and fairly weak when using dollar returns.

The last row of Table 1 presents the difference between portfolio golden betas and conventional betas. The pattern shows a linear decrease from 0.17 to -0.35 across portfolios. This suggests that the systematic risk of low-beta portfolios tends to be higher when returns are measured in gold rather than in dollars. Conversely, the systematic risk of high-beta portfolios tends to be lower when returns are measured in gold rather than in dollars.

Figure 2 plots average realized (excess) returns against unconditional betas for the 20 beta-sorted portfolios. With golden returns (Panel (a)), the intercept of the empirical Security Market Line (SML) is particularly close to zero, worth only 3 bps. The slope of the SML is 57 bps, aligning closely with the average golden return of the market worth 58 bps. The R^2 is 0.72, meaning that about three quarter of the variation in average returns is explained by beta. The results show that the empirical SML closely approximates the theoretical relationship predicted by the CAPM. The results are drastically different when using dollar returns. The intercept of the empirical SML is large, equal to 42 bps. The slope is only 28 bps, substantially lower than the average excess return of the market worth 56 bps. That is, the difference between the empirical SML and the theoretical SML is particularly pronounced when using dollar returns.

To test the CAPM, we run the following cross-sectional regressions

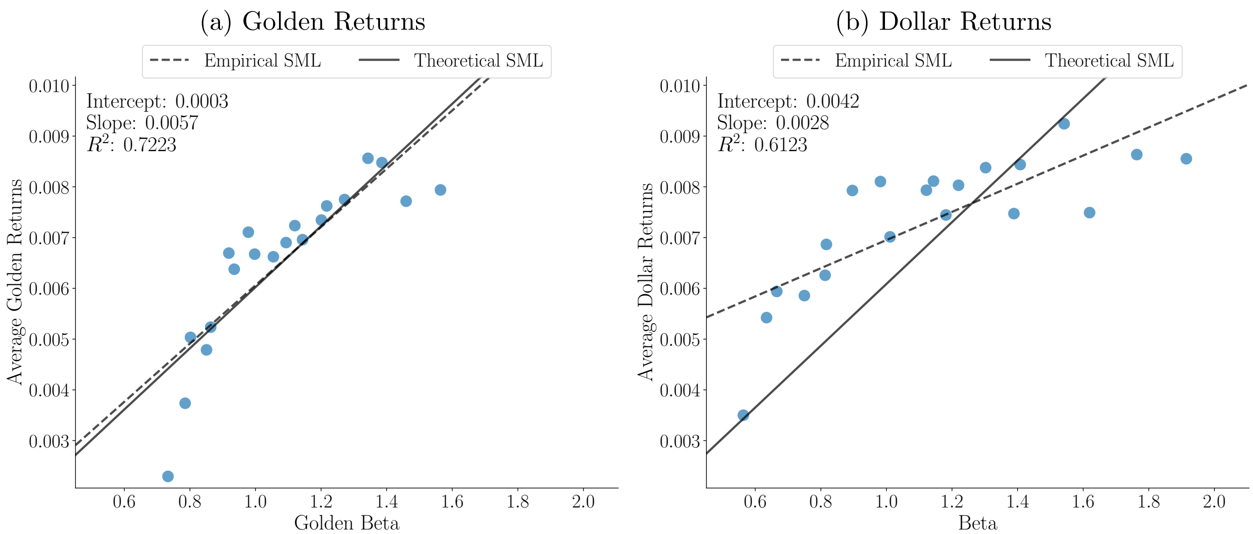
$$R_{p,t+1} - R_{f,t+1} = \gamma_0 + \gamma_1 \hat{\beta}_p + \epsilon_{t+1}, \tag{5}$$

and

$$R^{\mathbf{g}}_{p,t+1} = \gamma_0 + \gamma_1 \hat{\beta}^{\mathbf{g}}_p + \epsilon^{\mathbf{g}}_{t+1}, \tag{6}$$

where $R_{p,t+1}$ (resp., $R^{\mathbf{g}}_{p,t+1}$) is portfolio p dollar (resp., golden) return at time $t+1$, $R_{f,t+1}$ is the dollar risk-free rate, $\hat{\beta}_p$ (resp., $\hat{\beta}^{\mathbf{g}}_p$) is portfolio p unconditional beta estimated using

Figure 2: Average Monthly Returns versus Beta for 20 β-Sorted Portfolios
This figure plots average monthly value-weighted (excess) returns against market beta for the 20 beta-sorted portfolios. The data is from July 1927 to December 2024. Portfolios are rebalanced each month, with stocks sorted according to their prior beta, estimated using monthly returns over a three-year rolling window. Panel (a) shows the relationship between portfolios' average golden returns and beta. Panel (b) shows the relationship between portfolios' average dollar excess returns and beta. The solid line represents the theoretical relation predicted by the CAPM, i.e, the theoretical Security Market Line (SML). The dashed line is the linear regression fit of the data, i.e., the empirical SML. We further report the estimated intercept, slope, and R^2 of the linear fit.



dollar (resp., golden) returns, and ϵ_{t+1} and $\epsilon^{\mathbf{g}}_{t+1}$ are error terms. Regression (5) is performed using dollar returns and therefore tests the CAPM (1), whereas regression (6) is performed using golden returns and therefore tests the golden CAPM (3).

The left-hand side of Table 2 reports the results of the Fama and MacBeth (1973) regressions, and the right-hand side those of the pooled regressions with clustered standard errors. With golden returns (Panel A), the intercept is only 3 bps and not statistically different from zero. The slope is 57 bps, statistically significant, and remarkably close to the average market return worth 58 bps. That is, the golden CAPM is not rejected by the data. In stark contrast, with dollar returns (Panel B) the intercept is substantially larger (41 bps) and highly statistically significant. The slope is only 28 bps, substantially lower than the average market return, and not statistically significant according to the Fama-MacBeth regression. The large, significant intercept and small, insignificant slope of SML obtained with dollar returns provides direct evidence against the CAPM, as previously documented by Black et al. (1972), Fama and French (1992), and Fama and French (2004).

As a robustness check, we use in Section 4.1 24-, 48-, and 60-month rolling windows when

Table 2: Fama-MacBeth and Pooled Regressions for 20 β-Sorted Portfolios
This table presents estimates from Fama-MacBeth and pooled regressions of monthly value-weighted returns on betas for the 20 beta-sorted portfolios. The data is from July 1927 to December 2024. Panel A shows results of monthly golden returns on betas. Panel B shows results of monthly dollar excess returns on betas. t-statistics are reported in parentheses. For the Fama-MacBeth regressions, they are calculated using the standard deviation of the time-series estimates. For the pooled regressions, they are calculated using clustered standard errors. ***, **, and * indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

Fama-MacBeth Regression			**Pooled Regression**		
Intercept (γ_0)	Beta (γ_1)	Average R^2	Intercept (α)	Beta (β)	R^2
Panel A: Golden Returns					
0.0003	0.0057*	0.3340	0.0003	0.0057***	0.0003
(0.1185)	(1.8284)		(0.2339)	(5.1992)	
Panel B: Dollar Returns					
0.0041***	0.0028	0.3699	0.0041***	0.0028***	0.0002
(3.0680)	(1.3514)		(5.4371)	(4.5875)	

computing asset betas. We also sort stocks into 10 or 50 equal-populated portfolios, and we rebalance portfolios annually on Jannuary 1 (Black et al., 1972; Fama and French, 2004). These alternative procedures yield similar results, consistently supporting the validity of the golden CAPM.

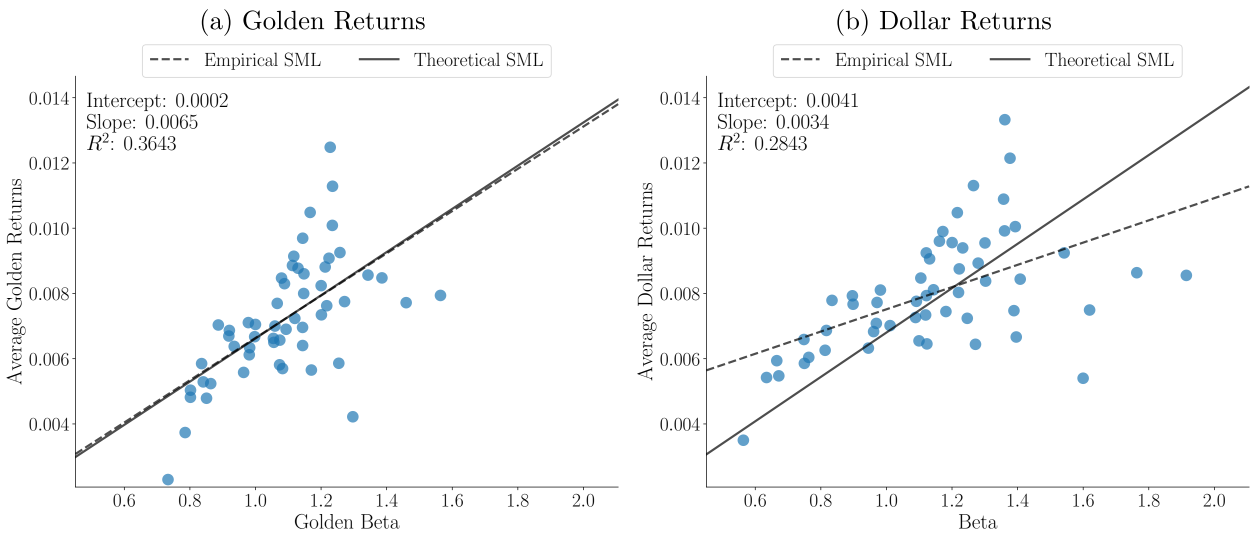
3.3 Size, Book-to-Market, and Industry Portfolios

In this section, we repeat our analysis by adding the 25 Fama-French size- and book-to-market-sorted portfolios and ten industry-sorted portfolios to the 20 beta-sorted portfolios used so far. Because the three sets of portfolios are formed according to very different characteristics, this analysis provides an important robustness test confirming the validity of our results.

Figure 3 plots the relationship between average realized (excess) returns and unconditional betas for all 55 test portfolios.[9] With golden returns (Panel (a)), the intercept is only 2 bps, and the slope is 65 bps. In contrast, with dollar returns (Panel (b)) the intercept is as large as 42 bps, and the slope is only 28 bps. That is, the alignment between the empirical

[9] Figures A1 and A2 in Appendix show the average-return-beta relationship separately for the 25 size- and book-to-market-sorted portfolios and ten industry-sorted portfolios, respectively.

Figure 3: Average Monthly Returns versus Beta for All 55 Test Portfolios
This figure plots average monthly value-weighted (excess) returns against market beta for all 55 test portfolios. The data is from July 1927 to December 2024. Panel (a) shows the relationship between portfolios' average golden returns and beta. Panel (b) shows the relationship between portfolios' average dollar excess returns and beta. The solid line represents the theoretical relation predicted by the CAPM, i.e, the theoretical Security Market Line (SML). The dashed line is the linear regression fit of the data, i.e., the empirical SML. We further report the estimated intercept, slope, and R^2 of the linear fit.



and theoretical SMLs is far better with golden returns than dollar returns. Confirming the results of Section 3.2 and in line with the prediction of the golden CAPM, golden returns produce an intercept close to zero and a slope that closely aligns with the average market return. In contrast, dollar returns produce a large intercept and a flat slope, consistent with the well-documented failure of the CAPM.

Table 3 presents the results of the Fama-MacBeth and pooled regressions applied to all 55 test portfolios. Panel A shows the results obtained with golden returns. Both the Fama-MacBeth and pooled regressions yield an intercept of only 1 bp, statistically indistinguishable from zero. The slope is economically large (64 bps), statistically significant, and statistically indistinguishable from the 58-bp average return of the market. Panel B shows the results obtained with dollar returns. Consistent with our previous findings, both the Fama-MacBeth and pooled regressions yield a high and statistically significant intercept of 41 bps. The slope is only 34 bps, substantially smaller than the average market return, and not statistically different from zero according to the Fama-MacBeth regression.

Tables A1 and A2 in Appendix report the equivalent of Table 3 but using separately the 25 Fama-French size- and book-to-market-sorted portfolios and ten industry portfolios, respectively. The results are in line with those reported in Table 3.

Table 3: Fama-MacBeth and Pooled Regressions for All 55 Test Portfolios
This table presents estimates from Fama-MacBeth and pooled regressions of monthly value-weighted returns on betas for all 55 test portfolios. The data is from July 1927 to December 2024. Panel A shows results of monthly golden returns on betas. Panel B shows results of monthly dollar excess returns on betas. t-statistics are reported in parentheses. For the Fama-MacBeth regressions, they are calculated using the standard deviation of the time-series estimates. For the pooled regressions, they are calculated using clustered standard errors. ***, **, and * indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

Fama-MacBeth Regression			**Pooled Regression**		
Intercept (γ_0)	Beta (γ_1)	Average R^2	Intercept (α)	Beta (β)	R^2
Panel A: Golden Returns					
0.0001	0.0064**	0.1987	0.0001	0.0064***	0.0002
(0.0564)	(1.9681)		(0.1048)	(4.7390)	
Panel B: Dollar Returns					
0.0041**	0.0034	0.2187	0.0041***	0.0034***	0.0002
(2.9545)	(1.5945)		(4.5339)	(3.8839)	

Consistent with the results obtained in Section 3.2, the current section shows that golden betas explain remarkably well the level of expected golden returns, whereas traditional betas fail to explain the level of expected dollar returns. That is, the golden CAPM holds, whereas the traditional CAPM fails.

3.4 Conditional Betas

One common criticism of the CAPM is its assumption of a single-period investment horizon. Therefore, Merton (1973) extends the framework by allowing agents to trade continuously over time. In this dynamic setting, the vector of asset returns has both a stochastic mean and a stochastic variance-covariance matrix. That is, market betas are allowed to be non-constant. Building on this theoretical motivation, Jagannathan and Wang (1996) provide empirical evidence that the conditional CAPM demonstrates substantially improved explanatory power for the cross-section of expected returns. The authors argue that the unconditional CAPM fails because it does not account for business cycle variations in systematic risk. They show that a company's sensitivity to market movements varies significantly with economic conditions. This suggests that the assumption of constant betas over time is problematic. Lettau and Ludvigson (2001) extend this work by showing that consumption-related conditioning variables can resurrect the CAPM's performance. Avramov and Chordia (2006) demonstrate that conditional models can explain many well-documented market anomalies that unconditional models fail to explain. Hasler and Martineau (2023) provide further evidence that the failure of the unconditional CAPM can actually be explained by the success of the conditional CAPM.

Given existing evidence that the assumption of constant betas is a limitation of the CAPM, this section examines whether allowing for time-varying risk exposures can further enhance the explanatory power of the golden CAPM relative to its unconditional analogue. We repeat the steps described in Section 3.1 with one minor change. At each time t, portfolio p conditional betas ($\hat{\beta}^{W}_{p,t}$ and $\hat{\beta}^{W,\mathbf{g}}_{p,t}$) are estimated using the most recent W monthly returns, for $W = 24$, 36, 48, 60, and 120, equivalent to 2, 3, 4, 5, and 10 years, respectively.

Table 4 reports the results of the Fama-MacBeth regressions (left-hand side) and pooled regressions (right-hand side) satisfying

$$R_{p.t+1} - R_{f,t+1} = \gamma_0 + \gamma_1 \hat{\beta}^{W}_{p,t} + \epsilon_{t+1}$$

when using dollar returns (Panel B), or

$$R^{\mathbf{g}}_{p.t+1} = \gamma_0 + \gamma_1 \hat{\beta}^{W,\mathbf{g}}_{p,t} + \epsilon^{\mathbf{g}}_{t+1}$$

when using golden returns (Panel A). With golden returns, Fama-MacBeth regressions yield intercepts that are close to zero and statistically insignificant. The slopes are large and statistically significant, ranging from 49 bps to 73 bps. The explanatory power improves marginally as the estimation window W lengthens, with average R^2 increasing from about 0.3 with $W = 24$ months to about 0.33 with $W = 120$ months.

The pooled regressions show that the intercepts obtained with golden returns (Panel A) are about half those obtained with dollar returns (Panel B). Intercepts obtained with golden returns range between 11 and 22 bps when the beta estimation window is 5 years or less. However, the intercept is negligible, equal to only 1 bp, and statistically insignificant when the beta estimation window is 10 years. The slopes obtained with golden returns are about twice as large as those obtained with dollar returns. The slope of 59 bps obtained with golden returns and a beta estimation window of 10 years is remarkably close to the average market return worth 58 bps. This confirms our previous findings that using golden returns significantly increases the performance of the model by mitigating the pricing distortions inherent in dollar-denominated returns.

Overall, the performance of the conditional CAPM is sensitive to the choice of the beta estimation window. When the estimation window is relatively long (10 years or more), the

Table 4: Fama-MacBeth and Pooled Regressions with Conditional Betas
This table presents estimates from Fama-MacBeth and pooled regressions of monthly value-weighted (excess) returns on conditional betas for 20 beta-sorted portfolios. The data is from July 1927 to December 2024. Each month, we estimate portfolios' rolling betas using a trailing window of W past monthly returns. Panel A shows results of monthly golden returns on beta. Panel B shows results of monthly dollar excess returns on beta. t-statistics are reported in parentheses. For the Fama-MacBeth regressions, they are calculated using the standard deviation of the time-series estimates. For the pooled regressions, they are calculated using clustered standard errors. ***, **, and * indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

	Fama-MacBeth Regression			**Pooled Regression**		
W	Intercept (γ_0)	Beta (γ_1)	Average R^2	Intercept (α)	Beta (β)	R^2
Panel A: Golden Returns						
24	0.0010	0.0049*	0.3006	0.0022***	0.0039***	0.0002
	(0.4034)	(1.6551)		(2.6116)	(6.4012)	
36	-0.0002	0.0060*	0.3104	0.0022***	0.0039***	0.0002
	(-0.0598)	(1.8381)		(3.0172)	(6.7784)	
48	-0.0014	0.0071**	0.3170	0.0011**	0.0050***	0.0003
	(-0.4667)	(2.0401)		(2.0010)	(9.4143)	
60	-0.0016	0.0073**	0.3200	0.0017***	0.0044***	0.0003
	(-0.5073)	(2.0026)		(2.7867)	(7.6954)	
120	-0.0003	0.0060*	0.3260	0.0001	0.0059***	0.0004
	(-0.0891)	(1.6860)		(0.0687)	(4.7935)	
Panel B: Dollar Returns						
24	0.0041***	0.0026	0.3529	0.0048***	0.0022***	0.0002
	(3.0839)	(1.2703)		(8.9056)	(5.2942)	
36	0.0042***	0.0025	0.3627	0.0047***	0.0022***	0.0002
	(3.0707)	(1.1877)		(8.1511)	(4.8271)	
48	0.0039***	0.0028	0.3667	0.0046***	0.0024***	0.0002
	(2.8267)	(1.2944)		(8.4586)	(5.4680)	
60	0.0036**	0.0031	0.3680	0.0049***	0.0024***	0.0002
	(2.5439)	(1.4164)		(7.7845)	(4.7611)	
120	0.0040***	0.0027	0.3696	0.0031***	0.0038***	0.0004
	(2.9216)	(1.2827)		(4.2700)	(5.3712)	

SML features a negligible intercept and a slope that is particularly close to the average market return. That is, the golden CAPM cannot be rejected by the data. One potential explanation is that the true betas are in fact constant. As a result, estimated conditional betas are noisy proxies for the true constant betas. Short beta estimation windows amplify this noise and distort asset-pricing tests.

3.5 Multi-Factor Models

Sections 3.2 and 3.3 show that the golden CAPM explains the level of asset returns. That is, the golden CAPM holds. This section extends the previous analysis by examining whether other asset-pricing models capture expected returns better than the golden CAPM. While there may be controversy over what is the best model to price assets,[10] the Fama and French (1993) three-factor (FF3) model has for decades established itself as a strong benchmark in asset pricing. Numerous studies have identified anomalies that violate the FF3 model, but only a few of them contended for status as additional factors. The momentum effect of Jegadeesh and Titman (1993) turns out to be one of those anomalies challenging the FF3 model. Thus, following Carhart (1997), the momentum factor is often added to the Fama–French three-factor model, resulting in the Carhart four-factor (FFC4) model. Fama and French (2015) propose the inclusion of two new factors based on investment and profitability to their former FF3 model, creating a five-factor (FF5) model. Fama and French (2018) further propose a six-factor model that adds the momentum factor (FF6). These models are natural benchmarks for evaluating asset-pricing performance.

Furthermore, Lewellen et al. (2010) document that the choice of test assets has an important impact on the performance of a model. For example, Fama and French (1993) show that the FF3 model captures the returns on portfolios formed on size and book-to-market (BM/ME) ratios but fails to explain the returns on portfolios sorted by size and market beta (Fama and French, 1993, 1996). When portfolios are constructed based on characteristics, it is implicitly assumed that expected returns are correlated with these characteristics. However, Daniel and Titman (1997) document that characteristic-sorted portfolios may not capture the covariance structure that drives returns. The authors show that firm characteristics themselves, rather than their return correlation with systematic risk factors, explain cross-sectional return variation. Daniel, Mota, Rottke, and Santos (2020) further demonstrate that characteristic-based factors can predict future returns, but these factors do not generally span the mean-variance efficient frontier. That is, characteristic-sorted portfolios perform well in explaining returns of portfolios sorted on the same characteristics but fail to

[10] See Hou, Xue, and Zhang (2014), Stambaugh and Yuan (2016), Daniel, Hirshleifer, and Sun (2019), Hou, Mo, Xue, and Zhang (2018), and Hou, Mo, Xue, and Zhang (2020) among others.

explain the returns of portfolios sorted on different characteristics.

To alleviate the concern that our results are biased by the portfolio construction choice, we test the ability of different factor models to explain the returns of the 20 beta-sorted portfolios, 25 size- and book-to-market-sorted portfolios, and ten industry-sorted portfolios used thus far. Specifically, the returns of each portfolio are regressed on the different factors, according to:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p^M (R_{m,t} - R_{f,t}) + \beta_p^F F_t + \epsilon_{p,t} \tag{7}$$

and

$$R^{\mathbf{g}}_{p,t} = \alpha^{\mathbf{g}}_p + \beta_p^{M,\mathbf{g}} R^{\mathbf{g}}_{m,t} + \beta_p^{F,\mathbf{g}} F^{\mathbf{g}}_t + \epsilon^{\mathbf{g}}_{p,t}. \tag{8}$$

Equation (7) specifies the relation using dollar returns. $R_{p,t}$ and $R_{m,t}$ are the dollar returns of portfolio p and the market m, $R_{f,t}$ is the dollar risk-free rate, and F_t is the vector of factors, where $F \in \{HML,\ SMB,\ MOM,\ RMW,\ CMA\}$. β_p^M and β_p^F are factor loadings on the market excess return and factor F return.

Equation (8) specifies the relation using golden returns. $R^{\mathbf{g}}_{p,t}$ and $R^{\mathbf{g}}_{m,t}$ are portfolio p and market m golden returns, respectively. Because the factor premium is the return of a mimicking portfolio, the vector of golden factors premiums $F^{\mathbf{g}}_t$ is equal to the vector of dollar premiums F_t divided by the gross gold return $(1 + R_{gold,t})$.[11]

The intercept α_p (resp., $\alpha^{\mathbf{g}}_p$) and factor loadings β_p^M and β_p^F (resp., $\beta_p^{M,\mathbf{g}}$ and $\beta_p^{F,\mathbf{g}}$) are estimated over the sample period from July 1927 to December 2024 when using the market, SMB, HML, and MOM factors, and from July 1963 to December 2024 when using the more recent RMW and CMA factors.

An asset pricing model that successfully captures expected returns produces an intercept indistinguishable from zero in either regression (7) or regression (8). Thus, previous studies have often focused on the model's absolute alphas (Fama and French, 1993; Hou, Karolyi, and Kho, 2011; Hou et al., 2014; Fama and French, 2015; Stambaugh and Yuan, 2016; Fama and French, 2018), and the *GRS*-test developed by Gibbons, Ross, and Shanken (1989) of whether all intercepts from a set of regressions are jointly equal to zero. Barillas and Shanken (2016, 2018) argue that a model with smaller alphas is not always a better model, and that one should instead compare the maximum squared Sharpe ratio (Sh^2) achievable by a factor model. One potential concern is that adding factors mechanically increases the attainable Sh^2. Therefore, based on this measure a multi-factor model may dominate a nested model even though the added factors have no true explanatory power (Lewellen et al., 2010; Harvey, Liu, and Zhu, 2015; Barillas, Kan, Robotti, and Shanken, 2019). To test whether individual factors contribute to the explanatory power of a model, Hansen and

[11]See Appendix B.

Jagannatha (1997) propose a performance metric (HJ-distance) that measures the distance between the model's stochastic discount factor (SDF) and the set of all possible SDFs that correctly price the test assets.

Table 5 shows the results for 15 different combinations of portfolios sets and factor models, with either dollar returns (right-hand side) or golden returns (left-hand side). Using golden returns increases explanatory power for all sets of portfolios and models, almost unequivocally. That is, golden returns consistently enhance model performance, thereby improving the ability of all factor models to explain cross-sectional variation in returns.

In what follows, the focus is on golden returns. Panel A reports the results for the 20 beta-sorted portfolios. Among the five tested models, the CAPM shows the strongest performance. The average absolute alpha is only 6 bps with a GRS p-value of 0.88, thus not statistically significant. Adding additional factors increases the average absolute alpha in the range of 7 to 23 bps. Moreover, the GRS test shows that the alphas of the FF5 and FF6 models are significantly different from zero, with a p-value of 0.02 and 0.00 respectively. The CAPM also yields the lowest value for $A|\alpha_p|/A|r_p| = 49.81\%$. That is, measured in units of average portfolio return, the CAPM leaves 49.81% of golden returns unexplained. The FF5 and FF6 yield a ratio larger than one, indicating that intercepts are larger than average returns in absolute value. The HJ-distance further confirms the CAPM's superior performance, with the lowest value of 0.11. This is two times lower than that of the FF6 model, worth 0.26. Overall, these results confirm that the golden CAPM is the best model explaining the returns of the 20 beta-sorted portfolios.

Panel B reports the results for the 25 size- and book-to-market-sorted portfolios. Although all factor models are rejected based on the GRS test, adding factors helps decrease the average absolute alpha from 18 bps (CAPM) to 7 bps (FF6). Importantly, the HJ-distance shows that the CAPM dominates the FF5 and FF6 models, and tracks closely the performances of the FF3 and FFC4 models.

Panel C reports the results for the ten industry-sorted portfolios. The results are consistent with those from Panel A. The CAPM's average absolute alpha is only 8 bps with a p-value of 0.11, thus not statistically significant. Multi-factor models perform substantially worse. The average absolute intercepts increases linearly with the model complexity, from 10 bps (for FF3) to 16 bps (for FF6). However, they all show statistical significance with a p-value around zero. The HJ-distance also favors the CAPM, showing the lowest value of about 0.12. The inclusion of additional factors increases the model's pricing errors, with the FF3, FFC4, FF5, and FF6 HJ-distances being about two times that of the CAPM. Once again, these results suggest that CAPM shows the best performance in explaining asset returns.

Table 5: Model Performance Summary

This table tests the ability of CAPM, Fama-French three-factor model (*FF3*), Carhart four-factor model (*FFC4*), Fama-French five-factor model (*FF5*), and Fama-French six-factor model (*FF6*) to explain monthly (excess) returns on 20 beta-sorted portfolios (Panel A), 25 size- and book-to-market-sorted portfolios (Panel B), and ten industry-sorted portfolios (Panel C). The sample covers the period July 1927 to December 2024. *FF5* and *FF6* models covers the period July 1963 to December 2024. For each set of 10, 20 or 25 regressions, the table reports the *GRS* statistic and its p-value testing whether the expected values of intercept estimates are jointly equal to zero. We further report the average absolute intercepts ($A|\alpha_p|$), the average absolute intercepts over the average absolute portfolio returns ($\frac{A|\alpha_p|}{A|r_p|}$), and Hansen-Jagannathan distance (*HJ dist.*), which measures the model's pricing error.

	Golden Returns					**Dollar Returns**				
	GRS stat.	GRS p-value	$A\|\alpha_p\|$	$\frac{A\|\alpha_p\|}{A\|r_p\|}$	HJ dist.	GRS stat.	GRS p-value	$A\|\alpha_p\|$	$\frac{A\|\alpha_p\|}{A\|r_p\|}$	HJ dist.
Panel A: 20 Beta-Sorted Portfolios										
CAPM	0.6408	0.8840	0.0006	0.4981	0.1061	1.1749	0.2676	0.0013	1.2807	0.1442
FF3	0.9162	0.5653	0.0009	0.7237	0.1274	1.8658	0.0117	0.0014	1.3801	0.1823
FFC4	0.8876	0.6036	0.0007	0.5664	0.1282	1.3474	0.1397	0.0009	0.8420	0.1588
FF5	1.8009	0.0172	0.0018	1.4353	0.2314	2.2137	0.0018	0.0011	1.2555	0.2598
FF6	2.1436	0.0026	0.0023	1.8639	0.2555	1.9503	0.0078	0.0012	1.3803	0.2475
Panel B: 25 Size- and Book-to-Market-Sorted Portfolios										
CAPM	3.1437	0.0000	0.0018	1.0637	0.2632	3.4328	0.0000	0.0016	0.9345	0.2761
FF3	2.9935	0.0000	0.0011	0.6365	0.2580	3.4046	0.0000	0.0012	0.6965	0.2759
FFC4	2.6539	0.0000	0.0009	0.5250	0.2483	2.9668	0.0000	0.0010	0.5962	0.2640
FF5	2.3002	0.0003	0.0007	0.4986	0.2934	2.9847	0.0000	0.0008	0.5816	0.3385
FF6	2.0842	0.0016	0.0007	0.4861	0.2827	2.7094	0.0000	0.0008	0.5365	0.3273
Panel C: Ten Industry-Sorted Portfolios										
CAPM	1.5608	0.1130	0.0008	0.8708	0.1165	2.1171	0.0207	0.0010	1.1105	0.1362
FF3	3.1489	0.0005	0.0010	1.1313	0.1663	3.7086	0.0001	0.0012	1.2728	0.1809
FFC4	3.3548	0.0003	0.0012	1.3045	0.1754	3.6976	0.0001	0.0012	1.3701	0.1852
FF5	3.6830	0.0001	0.0016	2.1066	0.2324	4.0599	0.0000	0.0015	2.0003	0.2471
FF6	3.3533	0.0003	0.0016	2.1353	0.2244	3.5368	0.0001	0.0014	1.9798	0.2340

One potential concern is that our results are specific to the sample period. Table A4 in Appendix reports analogous results to those in Table 5, but with a sample period for the CAPM, FF3, and FFC4 from July 1963 to December 2024, as for the FF5 and FF6 models. Overall, Table A4 shows that the results presented in Table 5 are robust when considering the alternative sample period from July 1963 to December 2024.

As documented by Lewellen et al. (2010), Table 5 shows that the performance of a model is sensitive to the choice of the test assets. If we compare the results obtained for each set of portfolios and asset pricing models, then the model with the highest explanatory power is the CAPM applied to beta-sorted portfolios. That is, the golden CAPM not only explains the level of asset returns but also outperforms all other tested models when portfolios are constructed according to their theoretically relevant characteristics.

4 Additional CAPM Tests

This section provides robustness results. First, we use alternative methods to construct beta-sorted portfolios. Second, we adjust excess golden returns over the fixed dollar-gold convertibility period. Third, we compute unconditional betas over an expanding window instead of over the whole sample period. Fourth, as argued by Hou et al. (2020), we eliminate microcap stocks from the sample. Fifth, we exclude short-lived stocks from the sample. Overall, the results obtained are similar to those reported in Section 3.2.

4.1 Alternative Portfolio Constructions

One potential concern is that the results presented in Section 3.2 may be sensitive to the portfolio construction method. To address this concern, we consider alternative methods for constructing beta-sorted portfolios. We compute asset betas using rolling windows of 24, 48, or 60 past monthly returns instead of 36. We sort stocks into 10 or 50 portfolios instead of 20. Following Black et al. (1972) and Fama and French (2004), we rebalance portfolios annually on January 1 instead of monthly.

Table 6 reports the Fama-MacBeth and pooled regression results for six sets of beta-sorted portfolios using golden returns. Once again, for each set of portfolios, intercepts are economically small and not statistically different from zero. Their values range between 2 bps and 7 bps, and their t-statistics are lower than 0.43. The slopes range between 53 bps and 59 bps, with t-statistics of at least 1.74 in the Fama-MacBeth regressions and 3.42 in the pooled regressions. This shows remarkable consistency and close alignment with the average market return worth 58 bps.

Overall, our main results are robust to alternative portfolio construction methods. Irrespective of the method, the SML features a negligible intercept and a large slope, consistent with the prediction of the CAPM.

4.2 Adjusted Golden Excess Returns

During the classical gold standard and Bretton Woods system, the dollar was pegged to gold at a fixed rate. One potential concern therefore arises during this period. An investor could sell gold and invest the proceeds into a risk-free asset. This translates into $(1+R_f)$ dollars

Table 6: Fama-MacBeth and Pooled Regressions for Various β-Portfolios
This table presents estimates from Fama-MacBeth and pooled regressions of monthly value-weighted golden returns on betas for various beta-sorted portfolios. The data is from July 1927 to December 2024. Each month, stocks are assigned into N equally populated portfolios based on their most recent W-month rolling betas. The N beta-sorted portfolios are rebalanced either monthly or annually on January 1^{st}. t-statistics are reported in parentheses. For the Fama-MacBeth regressions, they are calculated using the standard deviation of the time-series estimates. For the pooled regressions, they are calculated using clustered standard errors. ***, **, and * indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

			Fama-MacBeth Regression			**Pooled Regression**		
W	N	Rebalancing	Intercept (γ_0)	Beta (γ_1)	Average R^2	Intercept (α)	Beta (β)	R^2
24	20	monthly	0.0002	0.0059*	0.3262	0.0002	0.0059***	0.0003
			(0.0575)	(1.8218)		(0.1032)	(4.3709)	
48	20	monthly	0.0007	0.0053*	0.3420	0.0007	0.0053***	0.0003
			(0.3152)	(1.7448)		(0.4288)	(3.4728)	
60	20	monthly	0.0006	0.0054*	0.3386	0.0006	0.0054***	0.0003
			(0.2551)	(1.7738)		(0.3363)	(3.4217)	
36	10	monthly	0.0003	0.0057*	0.4423	0.0003	0.0057***	0.0003
			(0.1170)	(1.8174)		(0.1880)	(4.2165)	
36	50	monthly	0.0002	0.0058*	0.2274	0.0002	0.0058***	0.0003
			(0.0664)	(1.8838)		(0.1354)	(5.4882)	
36	20	annually,	0.0002	0.0059*	0.3228	0.0002	0.0059***	0.0003
		on January 1^{st}	(0.0599)	(1.8491)		(0.1418)	(6.1794)	

next period, which could be converted back to gold. In other words, gold holdings earn a risk-free return during this fixed dollar-gold convertibility period. To take this into account, the golden CAPM Equation (3) is adjusted as follows:

$$\mathbb{E}[X^{\mathbf{g}}_{i,t}] = \beta^{\mathbf{g}}_i \times \mathbb{E}[X^{\mathbf{g}}_{m,t}], \text{ with } \beta^{\mathbf{g}}_i = \frac{\text{Cov}(X^{\mathbf{g}}_i, X^{\mathbf{g}}_m)}{\text{Var}(X^{\mathbf{g}}_m)} \tag{9}$$

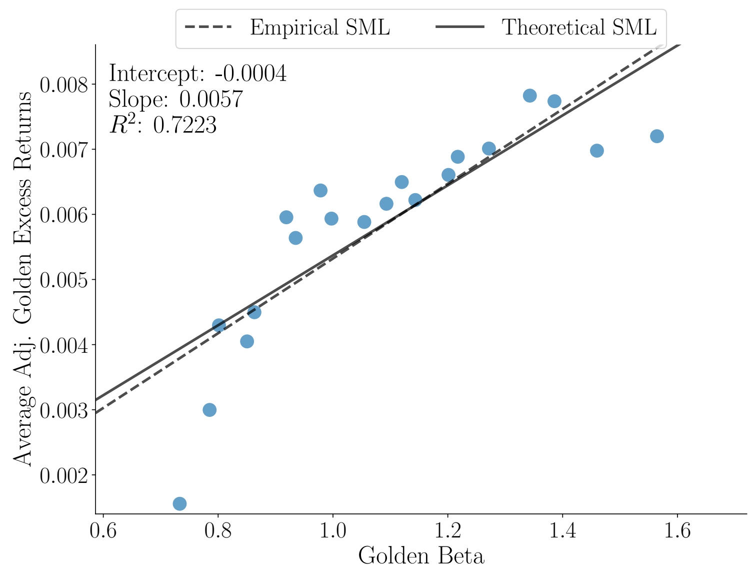
and

$$\begin{cases} X^{\mathbf{g}}_{i,t} = R^{\mathbf{g}}_{i,t} - R^{\mathbf{g}}_{f,t}, \qquad X^{\mathbf{g}}_{m,t} = R^{\mathbf{g}}_{m,t} - R^{\mathbf{g}}_{f,t} \quad \text{if July 1927} \leq t \leq \text{December 1971}, \\ X^{\mathbf{g}}_{i,t} = R^{\mathbf{g}}_{i,t}, \qquad X^{\mathbf{g}}_{m,t} = R^{\mathbf{g}}_{m,t} \quad \text{if } t > \text{December 1971}. \end{cases}$$

$X^{\mathbf{g}}$ denotes golden excess returns, and the golden risk-free rate satisfies $R^{\mathbf{g}}_{f,t} \equiv \frac{1+R_{f,t}}{1+R_{gold,t}} - 1$. The golden risk-free rate $R^{\mathbf{g}}_{f,t}$ is assumed to be equal to the dollar risk-free rate $R_{f,t}$ over the

Figure 4: Average Monthly Returns versus Beta with Adjusted Golden Excess Returns

This figure plots average monthly value-weighted adjusted golden excess returns against market beta for the 20 beta-sorted portfolios. The data is from July 1927 to December 2024. Portfolios are rebalanced each month, with stocks sorted according to their prior beta, estimated using monthly returns over a three-year rolling window. The solid line represents the theoretical relation predicted by the CAPM, i.e., the theoretical Security Market Line (SML). The dashed line is the linear regression fit of the data, i.e., the empirical SML. We further report the estimated intercept, slope, and R^2 of the linear fit.



period from July 1927 to December 1971. The reason is that we abstract from the January 1934 gold revaluation from \$20.67 to \$35 per ounce, thereby setting $R_{gold} = 0$ for the entire period from July 1927 to December 1971. In the golden CAPM (9), golden excess returns are adjusted to account for a non-zero risk-free return on gold holdings over the period from July 1927 to December 1971. Over the period from January 1972 to December 2024, golden excess returns are equal to golden returns because gold holdings earn a zero risk-free return.

Figure 4 provides preliminary evidence that the golden CAPM still holds under this adjustment. The results reported earlier in Section 3.2 are not affected by the period when the dollar was pegged to gold at a fixed rate. The intercept of the empirical SML is only -4 bps. The slope is 57 bps, once again close to the average golden excess return of the market worth 53 bps. The alignment between the empirical and theoretical SMLs remains strong when using adjusted golden excess returns.

Table 7 confirms these results. Both the Fama-MacBeth (left-hand side) and pooled regressions (right-hand side) yield an intercept of -4 bps, not statistically different from zero. The slope is 57 bps, it aligns well with the average golden excess return of the market

Table 7: Fama-MacBeth and Pooled Regressions with Adjusted Golden Excess Returns

This table presents estimates from Fama-MacBeth and pooled regressions of monthly value-weighted adjusted golden excess returns on betas for 20 beta-sorted portfolios. The data is from July 1927 to December 2024. t-statistics are reported in parentheses. For the Fama-MacBeth regressions, they are calculated using the standard deviation of the time-series estimates. For the pooled regressions, they are calculated using clustered standard errors. ***, **, and * indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

Fama-MacBeth Regression			**Pooled Regression**		
Intercept (γ_0)	Beta (γ_1)	Average R^2	Intercept (α)	Beta (β)	R^2
-0.0004	0.0057*	0.3340	-0.0004	0.0057***	0.0003
(-0.1760)	(1.8284)		(-0.3472)	(5.1997)	

worth 53 bps, and it is statistically different from zero. Overall, the adjustment made in this section to account for the non-zero risk-free return on gold holdings during the fixed dollar-gold convertibility period (July 1927–December 1971) does not alter the validity of the golden CAPM. The model continues to explain the cross-section of returns remarkably well, with an economically small and statistically insignificant intercept, and a slope that matches the average golden excess return of the market.

4.3 Expanding-Window Betas

The CAPM tests performed in Section 3.2 use betas estimated over the whole sample period from July 1927 to December 2024. This may raise concerns about the forward-looking bias in betas, which could in turn drive the conclusion that the golden CAPM holds. To show that the golden CAPM holds irrespective of this forward-looking bias, portfolio betas are estimated over an expanding window in the current section. That is, at each point in time, betas are computed using past returns only.[12] This implies that portfolio betas vary over time, but do so progressively less as more data becomes available.

Table 8 presents the results of the Fama-MacBeth and pooled regressions obtained with expanding-window betas. With golden returns (Panel A), the intercept is only 4 bps in the Fama-MacBeth regression and 3 bps in the pooled regression, both statistically indistinguishable from zero. The slope is 54 bps in both regressions, which is economically large, close to the average market return, and statistically significant.

[12] We require at least 36 past monthly returns to compute portfolio betas.

Table 8: Fama-MacBeth and Pooled Regressions with Expanding-Window Betas This table presents estimates from Fama-MacBeth and pooled regressions of monthly value-weighted golden returns on betas for 20 beta-sorted portfolios. Portfolio betas are estimated each month using an expanding window, requiring at least 36 past monthly returns. The data is consequently from July 1930 to December 2024. Panel A shows the results obtained with golden returns. Panel B shows the results obtained with adjusted golden excess returns (see Section 4.2). t-statistics are reported in parentheses. For the Fama-MacBeth regressions, they are calculated using the standard deviation of the time-series estimates. For the pooled regressions, they are calculated using clustered standard errors. ***, **, and * indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

Fama-MacBeth Regression			**Pooled Regression**		
Intercept (γ_0)	Beta (γ_1)	Average R^2	Intercept (α)	Beta (β)	R^2
Panel A: Golden Returns					
0.0004	0.0054**	0.3320	0.0003	0.0054***	0.0004
(0.1921)	(2.0185)		(0.3959)	(7.8368)	
Panel B: Adjusted Golden Excess Returns					
-0.0002	0.0053**	0.3321	-0.0001	0.0052***	0.0004
(-0.1002)	(2.0177)		(-0.1382)	(7.2290)	

With adjusted golden excess returns[13] (Panel B), the intercept is only −2 bps in the Fama-MacBeth regression and 1 bp in the pooled regression, both statistically indistinguishable from zero. The slope is economically large (53 or 52 bps), aligns well with the average market return, and is statistically significant.

These results show remarkable consistency. The golden CAPM performs well regardless of whether betas are estimated using the full sample or past data only. The intercept remains economically small and statistically insignificant. The slope remains economically large and statically significant, aligning closely with the average market return. Adjusting golden excess return to account for the fixed dollar-gold convertibility period does not materially affect the results. These findings highlight the robustness of the golden CAPM in explaining the cross-section of returns.

4.4 Exclusion of Noisy Assets

This section investigates the results obtained when excluding noisy assets. Hou et al. (2020) examine long-short portfolios formed based on various stock characteristics. The authors

[13]See Section 4.2 for the definition of adjusted golden excess returns.

Table 9: Size of Various Universes of Assets
This table presents the size of the various universes of assets. The data is from January 1926 to December 2024. *N firms* is the number of distinct firms per category. *% Mkt Cap* is the market capitalization of the category over the market capitalization of all firms. *Total Obs* is the number of month-firm observations per category (in millions).

	All Firms	Microcap	All-but-microcap	All-but-short-lived	All-but-medium-lived	All-but-short-lived-microcap	All-but-medium-lived-microcap
N firms	26696	23441	13187	16356	10152	9944	7112
% Mkt Cap	100.00	3.23	97.35	98.65	95.98	96.32	94.22
Total Obs	3.757	2.116	1.641	3.434	2.901	1.576	1.452

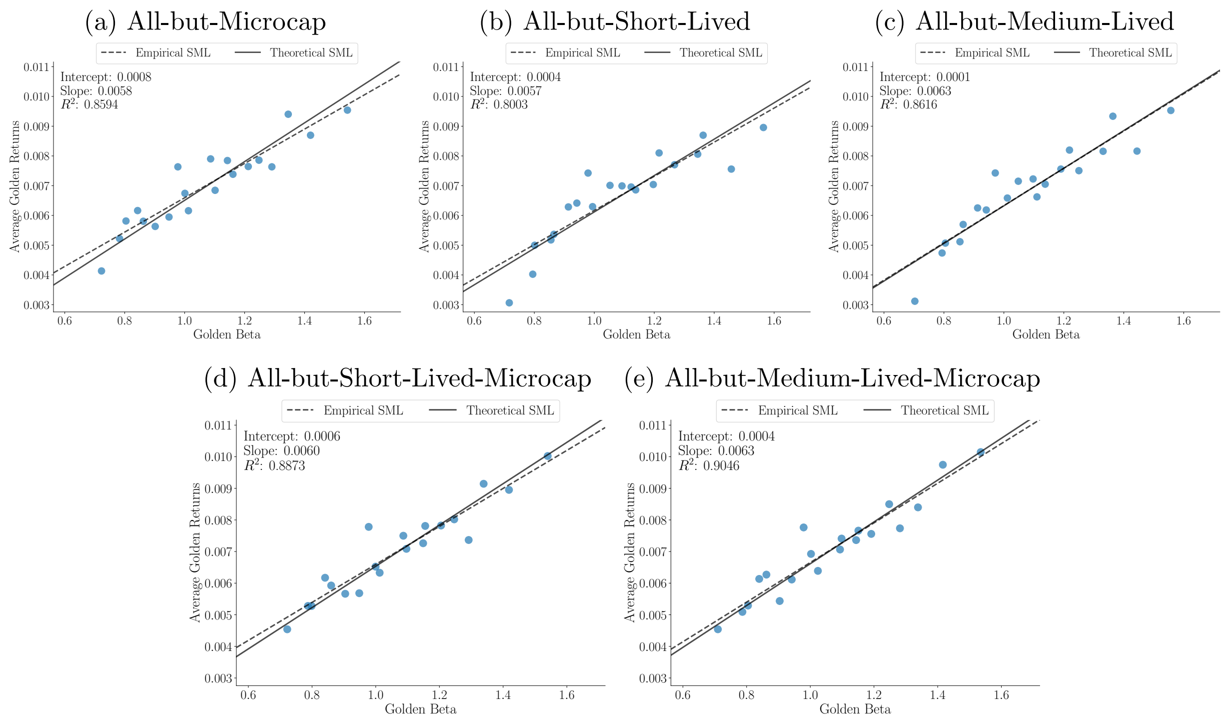
show that microcap stocks, those with a market capitalization smaller than the NYSE 20th percentile, are the main drivers of many asset-pricing anomalies. They suggest several ways to limit their impact. Table 9 shows that while microcap stocks account for only 3.23% of the aggregate market capitalization, they represent around 56.32% of the total number of observations (2.116 out of 3.757 millions). Thus, excluding microcap stocks introduces a trade-off between sample size and accuracy.

We propose a novel, yet intuitive, approach to exclude noisy assets. Instead of excluding all microcap stocks, only those that did not remain listed on the stock exchange beyond a specified period are excluded. Short-lived stocks (resp., medium-lived stocks) are thus defined as stocks who survived for at least 5 years (resp., 10 years) on the exchange.[14] For the sake of comparison, we also define microcap stocks as those with a market capitalization below the NYSE 20th percentile (Hou et al., 2020). In what follows, five universes of assets are considered: "*all-but-microcap*", "*all-but-short-lived*", "*all-but-medium-lived*", "*all-but-short-lived-microcap*", and "*all-but-medium-lived-microcap*".

The motivation to exclude short-lived stocks comes form the evidence that IPOs underperform relative to similar stocks for up to five years after going public (Ritter (1991) and Loughran and Ritter (1995) among others). Schultz (2003) shows that companies often issue equity at higher prices even though they are unable to predict future returns. Table 9 shows that only 16,356 firms survive at least 5 years on the exchange. This suggests that, for approximately 40% of stocks, the market may fail to efficiently price them due to poor trading history. These noisy assets account for only 1.35% of the aggregate market capitalization, and they represent 8.26% of the total observations. If we increase the minimum listing period to 10 years, the resulting subsample represents 95.98% of the total market capitalization, and 77.21% of the total observations (2.901 out of 3.757 millions). This is a substantially larger

[14]For short-lived stocks, stocks with less than 60 monthly observations (5 years) are excluded from the sample. For medium-lived stocks, stocks with less than 120 monthly observations (10 years) are excluded from the sample.

Figure 5: Average Monthly Returns versus Beta for Various Universes of Assets This figure plots average monthly value-weighted golden returns against market beta for the 20 beta-sorted portfolios. The data is from July 1927 to December 2024. Panel (a) shows the relationship between portfolios' average golden returns and beta for *all-but-microcap* stocks. Panel (b), (c), (d) and (e) shows the relationship for *all-but-short-lived*, *all-but-medium-lived*, *all-but-short-lived-microcap* and *all-but-medium-lived-microcap* stocks, respectively. The solid line represents the theoretical relation predicted by the CAPM, i.e, the theoretical Security Market Line (SML). The dashed line is the linear regression fit of the data, i.e., the empirical SML. We further report the estimated intercept, slope, and R^2 of the linear fit.



sample compared to that obtained by excluding microcap stocks. Indeed, *"all-but-microcap"* keeps only 43.68% of the total observations (1.641 out of 3.757 millions).

The tests performed in Section 3.2 are repeated here and applied to the aforementioned five universes of assets. For each universe of assets, at the beginning of each month, stocks are sorted into one of the 20 portfolios based on their past 36-month rolling betas. We use monthly value-weighted portfolio returns, and estimate for each portfolio its unconditional full-sample beta. Figure 5 Panel (a) shows that excluding microcap stocks has no significant impact on the golden CAPM's ability to explain average returns (see Figure 2 Panel (a) for the full sample comparison). However, the all-but-microcap universe of assets yields the golden CAPM's poorest performance among all five universes. Panels (b) and (c) provide preliminary evidence that, in terms of golden CAPM performance, the noisiest stocks are

Table 10: Fama-MacBeth and Pooled Regressions for Various Universes of Assets
This table presents estimates from Fama-MacBeth and pooled regressions of monthly value-weighted golden returns on betas for the 20 beta-sorted portfolios. The data is from July 1927 to December 2024. Panel A shows results for *all-but-microcap* stocks. Panel B, C, D, and E shows results for *all-but-short-lived*, *all-but-medium-lived*, *all-but-short-lived-microcap*, and for *all-but-medium-lived-microcap* stocks, respectively. t-statistics are reported in parentheses. For the Fama-MacBeth regressions, they are calculated using the standard deviation of the time-series estimates. For the pooled regressions, they are calculated using clustered standard errors. ***, **, and * indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

Fama-MacBeth Regression			**Pooled Regression**		
Intercept (γ_0)	Beta (γ_1)	Average R^2	Intercept (α)	Beta (β)	R^2
Panel A: All-but-Microcap					
0.0008	0.0057*	0.3383	0.0008	0.0057***	0.0003
(0.3142)	(1.8220)		(1.4063)	(11.4447)	
Panel B: All-but-Short-Lived					
0.0004	0.0057*	0.3347	0.0004	0.0057***	0.0003
(0.1650)	(1.8318)		(0.4515)	(7.2056)	
Panel C: All-but-Medium-Lived					
0.0000	0.0062**	0.3365	0.0000	0.0062***	0.0003
(0.0072)	(2.0043)		(0.0226)	(8.9597)	
Panel D: All-but-Short-Lived-Microcap					
0.0006	0.0060*	0.3360	0.0006	0.0060***	0.0003
(0.2218)	(1.9051)		(1.2483)	(14.8141)	
Panel E: All-but-Medium-Lived-Microcap					
0.0004	0.0062**	0.3326	0.0004	0.0062***	0.0003
(0.1415)	(1.9856)		(0.8012)	(15.8284)	

indeed those that were listed for short periods on the exchanges.

The Fama-MacBeth and pooled regression outputs reported in Table 10 further support these findings. Panel A reports the results for all-but-microcap stocks. The intercept is 8 bps and not statistically different from zero. The slope is 57 bps, closely matching the average market return of 58 bps, and statistically significant. While these results are statistically similar to those reported in Section 3.2, the intercept of the all-but-microcap universe is nearly three times that of the full sample (8 bps vs. 3 bps).

Panel B and C of Table 10 report the results obtained by excluding either short-lived stocks or medium-lived stocks, respectively. Excluding short-lived stocks yields an intercept of 4 bps and a slope of 57 bps, similar to the full sample (3 bps and 57 bps, respectively). The intercept is not statistically different from zero, whereas the slope is. Thus, the cross-sectional return variation of *all-but-short-lived* stocks is particularly well explained by their golden betas. The results are even stronger when we test the ability of the golden CAPM to explain the returns of *all-but-medium-lived* stocks. Panel C shows that the intercept is virtually zero with a t-statistic below 0.03, whereas the slope is 62 bps with a t-statistic above 2.00. That is, the predictions of the golden CAPM hold remarkably well when the test assets consist of stocks listed for at least 10 years.

Panel D and E of Table 10 report the results obtained by excluding either short-lived stocks and microcap stocks or medium-lived stocks and microcap stocks, respectively. Once again, the results are statistically similar to those obtained with all stocks (see Table 2 Panel A for comparison). The intercept obtained with all-but-short-lived-microcaps stocks is 6 bps and not statistically significant. The slope is 60 bps and statistically significant. The intercept obtained with all-but-medium-lived-microcaps is 4 bps and not statistically significant, whereas the slope is 62 bps and statistically significant.

Figure A3 and Table A6 in Appendix report the results obtained with dollar returns, analogous to those in Figure 5 and Table 10. In summary, excluding noisy assets yields results similar to those reported in Section 3.2. Indeed, traditional betas explain poorly the cross-section of dollar returns.

5 Conclusion

The CAPM predicts that differences in expected returns across assets are entirely explained by differences in market beta. However, empirical research has systematically uncover alternative variables that explain the level of asset returns not captured by beta (anomalies), thereby challenging the validity of the CAPM. We show that the CAPM holds when returns are measured in ounces of gold, as it was the case prior to 1971. Regressing asset golden returns on their golden betas yields an intercept that is economically small and statistically insignificant. In addition, the slope is economically large, closely aligns with the average market return, and is statistically significant. That is, the golden CAPM cannot be rejected by the data. We further show that excluding microcap stocks or short-lived stocks (stocks listed for less than 5 or 10 years) does not affect the CAPM's ability to explain the cross-section of returns. In fact, excluding stocks listed for less than 10 years yields an intercept of 0 bps and a large slope, aligning remarkably well with the prediction of the CAPM.

These findings carry important implications for both academic research and practical applications. Our results suggest that apparent violations of the CAPM may reflect monetary distortions rather than fundamental failures in the risk-return relationship. This insight should help practitioners refine their use of the CAPM when computing the cost of capital or building investment strategies (Graham and Harvey, 2001; Berk and van Binsbergen, 2016), particularly in periods of monetary instability. Also, the success of the golden CAPM suggests that asset returns should be benchmarked in ounces of gold, rather than in U.S. dollars, when evaluating anomalies or asset pricing models.

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Appendix

A Transformation of *Dollar*-Denominated Portfolio Returns to *Gold*-Denominated Returns

We begin by defining the dollar return of a portfolio p at time t as the value-weighted sum of its N constituent assets:

$$R_{p,t} = \sum_{i=1}^{N} w_{i,t-1}\, R_{i,t}, \quad \text{where} \quad w_{i,t-1} = \frac{\text{ME}_{i,t-1}}{\sum_{j=1}^{N} \text{ME}_{j,t-1}}$$

Here, $R_{i,t}$ denotes the dollar return of asset i at time t, and $w_{i,t-1}$ is its weight in the portfolio, based on its most recent market equity $\text{ME}_{i,t-1}$.

Next, the portfolio p golden return, denoted $R^{\mathbf{g}}_{p,t}$, can similarly be expressed as the weighted average of its constituents' golden returns:

$$R^{\mathbf{g}}_{p,t} = \sum_{i=1}^{N} w_{i,t-1}\, R^{\text{gold}}_{i,t}, \tag{10}$$

where the golden return of asset i at time t, $R^{\mathbf{g}}_{i,t}$, is given by:

$$R^{\mathbf{g}}_{i,t} = \frac{1 + R_{i,t}}{1 + R_{\text{gold},t}} - 1, \tag{11}$$

with $R_{i,t}$ equals the asset i dollar return and $R_{\text{gold},t}$ is the return on one ounce of gold over the same time.

Substituting Equation (11) into (10) yields:

$$\begin{aligned} R^{\mathbf{g}}_{p,t} &= \sum_{i=1}^{N} w_{i,t-1}\left(\frac{1 + R_{i,t}}{1 + R_{\text{gold},t}} - 1\right) = \sum_{i=1}^{N} w_{i,t-1}\frac{1 + R_{i,t}}{1 + R_{\text{gold},t}} - \sum_{i=1}^{N} w_{i,t-1} \\ &= \frac{1}{1 + R_{\text{gold},t}} \sum_{i=1}^{N} w_{i,t-1}(1 + R_{i,t}) - 1 = \frac{1 + R_{p,t}}{1 + R_{\text{gold},t}} - 1. \end{aligned} \tag{12}$$

B Transformation of *Dollar*-Denominated Factor Premiums to *Gold*-Denominated Premiums

Consider a classical factor m premium, defined at time t as the difference in (average) returns between two (or more) extreme characteristic-sorted portfolios:

$$F_{m,t} = \bar{R}^m_{e,t} - \bar{R}^m_{E,t},$$

where $\bar{R}^m_{e,t}$ and $\bar{R}^m_{E,t}$ denote the dollar (average) returns of the bottom and top (or vice versa) portfolios sorted on characteristic m.

Analogously, the golden factor premium is the difference between the golden (average) returns of these extreme portfolios:

$$F^{\mathbf{g}}_{m,t} = \bar{R}^{\mathbf{g},m}_{e,t} - \bar{R}^{\mathbf{g},m}_{E,t}.$$

Substituting the portfolio golden return with its dollar return from Equation (12), we obtain:

$$\begin{aligned} F^{\mathbf{g}}_{m,t} &= \left(\frac{1 + \bar{R}^m_{e,t}}{1 + R_{\text{gold},t}} - 1 \right) - \left(\frac{1 + \bar{R}^m_{E,t}}{1 + R_{\text{gold},t}} - 1 \right) \\ &= \frac{\bar{R}^m_{e,t} - \bar{R}^m_{E,t}}{1 + R_{\text{gold},t}} = \frac{F_{m,t}}{1 + R_{\text{gold},t}}. \end{aligned}$$

Thus, the factor m premium in ounces of gold is equal to the dollar factor premium over the gross (one plus the rate of) return on gold.

C Traditional vs. Golden Return and Beta

Let P_i and R_i be respectively the price (total-return price including reinvested dividends) and return of asset i denominated in dollars. Let $P^{\mathbf{g}}_i$ and $R^{\mathbf{g}}_i$ be respectively the price and return of asset i denominated in ounces of gold. The golden return $R^{\mathbf{g}}_{i,t}$ satisfies

$$\begin{aligned} R^{\mathbf{g}}_{i,t} &\equiv \frac{P^{\mathbf{g}}_{i,t}}{P^{\mathbf{g}}_{i,t-1}} - 1 \\ &= \frac{P_{i,t}/P_{gold,t}}{P_{i,t-1}/P_{gold,t-1}} - 1 \\ &= \frac{P_{i,t}/P_{i,t-1}}{P_{gold,t}/P_{gold,t-1}} - 1 \\ &= \frac{1+R_{i,t}}{1+R_{gold,t}} - 1, \end{aligned}$$

where P_{gold} is the price of one ounce of gold denominated in dollars, and R_{gold} is the return of one ounce of gold denominated in dollars.

Let r_i and $r^{\mathbf{g}}_i$ denote the log return of asset i denominated in dollars and ounces of gold, respectively. The log golden return $r^{\mathbf{g}}_i$ satisfies:

$$\begin{aligned} r^{\mathbf{g}}_{i,t} &= log\left(1+R^{\mathbf{g}}_{i,t}\right) \\ &= log\left(\frac{1+R_{i,t}}{1+R_{gold,t}}\right) \\ &= r_{i,t} - r_{gold,t}, \end{aligned} \tag{13}$$

where r_{gold} is the log return of one ounce of gold denominated in dollars. Similarly, the log golden return of the market $r^{\mathbf{g}}_m$ satisfies:

$$r^{\mathbf{g}}_{m,t} = r_{m,t} - r_{gold,t}. \tag{14}$$

Decomposition of golden beta, $\beta_i^{\mathbf{g}}$. Substituting the returns from Equation (13) and (14), the golden beta of asset i satisfies:

$$\begin{aligned}
\beta_i^{\mathbf{g}} =& \frac{Cov(r_i^{\mathbf{g}}, r_m^{\mathbf{g}})}{Var(r_m^{\mathbf{g}})} \\
=& \frac{Cov(r_i, r_m) - Cov(r_i, r_{gold}) - Cov(r_{gold}, r_m) + Var(r_{gold})}{Var(r_m^{\mathbf{g}})} \\
=& \frac{Var(r_m)}{Var(r_m^{\mathbf{g}})}\beta_i - \frac{Var(r_{gold})}{Var(r_m^{\mathbf{g}})}\beta_i^{gold} + \frac{Var(r_{gold}) - Cov(r_{gold}, r_m)}{Var(r_m^{\mathbf{g}})} \\
=& \frac{Var(r_m)}{Var(r_m) + Var(r_{gold}) - 2Cov(r_m, r_{gold})}\beta_i - \frac{Var(r_{gold})}{Var(r_m) + Var(r_{gold}) - 2Cov(r_m, r_{gold})}\beta_i^{gold} \\
& + \frac{Var(r_{gold}) - Cov(r_{gold}, r_m)}{Var(r_m) + Var(r_{gold}) - 2Cov(r_m, r_{gold})},
\end{aligned}$$

where $\beta_i^{gold} \equiv \frac{Cov(r_i, r_{gold})}{Var(r_{gold})}$ is the exposure of the dollar-denominated return of asset i to the dollar-denominated return of the ounce of gold.

Assuming that the correlation between the dollar-denominated return of the market and the dollar-denominated return of one ounce of gold is close to zero ($Cov(r_m, r_{gold}) \approx 0$), the golden beta simplifies to:

$$\beta_i^{\mathbf{g}} \approx \frac{Var(r_m)}{Var(r_m) + Var(r_{gold})}\beta_i - \frac{Var(r_{gold})}{Var(r_m) + Var(r_{gold})}\beta_i^{gold} + \frac{Var(r_{gold})}{Var(r_m) + Var(r_{gold})}.$$

D Figures and Tables

Table A3 reports summary statistics for the 25 size- and book-to-market-sorted portfolios in Panel A. Average golden returns increase from 42 bps to 88 bps (5.04% to 10.56% annually), however the spread is lower compared to beta-sorted portfolios (from 23 bps to 79 bps). Moreover, golden betas vary less across portfolios, ranging from 0.96 to 1.30. Average dollar returns range between 81 bps and 122 bps (9.72% and 14.64% annually), while betas range between 0.94 and 1.60. Table A1 presents the results from Fama-MacBeth and pooled regressions for the 25 size- and book-to-market sorted portfolios. With golden returns, the intercept is only -10 bps, while the slope is as large as 79 bps. With dollar returns, the intercept is as large as 42 bps and the slope is only 37 bps, substantially lower than the average market return. Although none of the coefficients reported in Table A1 are statistically significant, it is clear that using golden returns substantially reduces the economic magnitude of the intercept and substantially increases that of the slope.

Panel B of Table A3 shows that industry portfolios exhibit stronger beta variation than the 25 size- and book-to-market-sorted portfolios. Golden betas range from 0.80 to 1.20, and average golden returns increase from 48 bps to 82 bps (5.76% to 9.84% annually). Using dollar returns, betas range from 0.67 to 1.28, and average returns range from 82 bps to 116 bps (9.84% and 13.92% annually). Table A2 shows regressions results for the ten industry-sorted portfolios. With golden returns (Panel A), the intercept is only 9 bps and not statistically significant. The slope is 57 bps, aligning closely with the average golden return of the market worth 58 bps. The slope is statistically significant according to the pooled regression. With dollar returns (Panel B), the intercept is as large as 35 bps and statistically significant. The slope is only 38 bps, substantially lower than the average market return. Once again, the golden CAPM holds, whereas the traditional CAPM fails.

Overall, golden returns consistently improve the explanatory power of the CAPM. That is, the choice of the monetary unit matters when testing the validity of the CAPM.

Figure A1: Average Monthly Returns versus Beta for 25 Size- and Book-to-Market-Sorted Portfolios

This figure plots average monthly value-weighted (excess) returns against market beta for the 25 Fama and French size- and book-to-market-sorted portfolios. The data is from July 1927 to December 2024. Panel (a) shows the relationship between portfolios' average golden returns and beta. Panel (b) shows the relationship between portfolios' average dollar excess returns and beta. The solid line represents the theoretical relation predicted by the CAPM, i.e, the theoretical Security Market Line (SML). The dashed line is the linear regression fit of the data, i.e., the empirical SML. We further report the estimated intercept, slope, and R^2 of the linear fit.

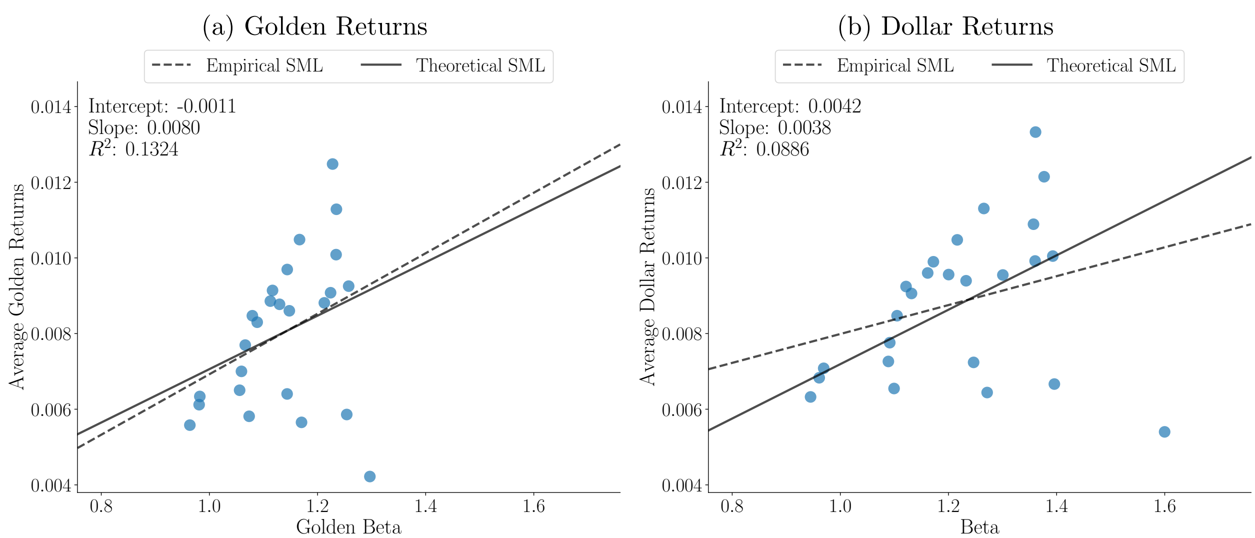

Figure A2: Average Monthly Returns versus Beta for Ten Industry-Sorted Portfolios

This figure plots average monthly value-weighted (excess) returns against market beta for the ten Industry-sorted portfolios. The data is from July 1927 to December 2024. Panel (a) shows the relationship between portfolios' average golden returns and beta. Panel (b) shows the relationship between portfolios' average dollar excess returns and beta. The solid line represents the theoretical relation predicted by the CAPM, i.e, the theoretical Security Market Line (SML). The dashed line is the linear regression fit of the data, i.e., the empirical SML. We further report the estimated intercept, slope, and R^2 of the linear fit.

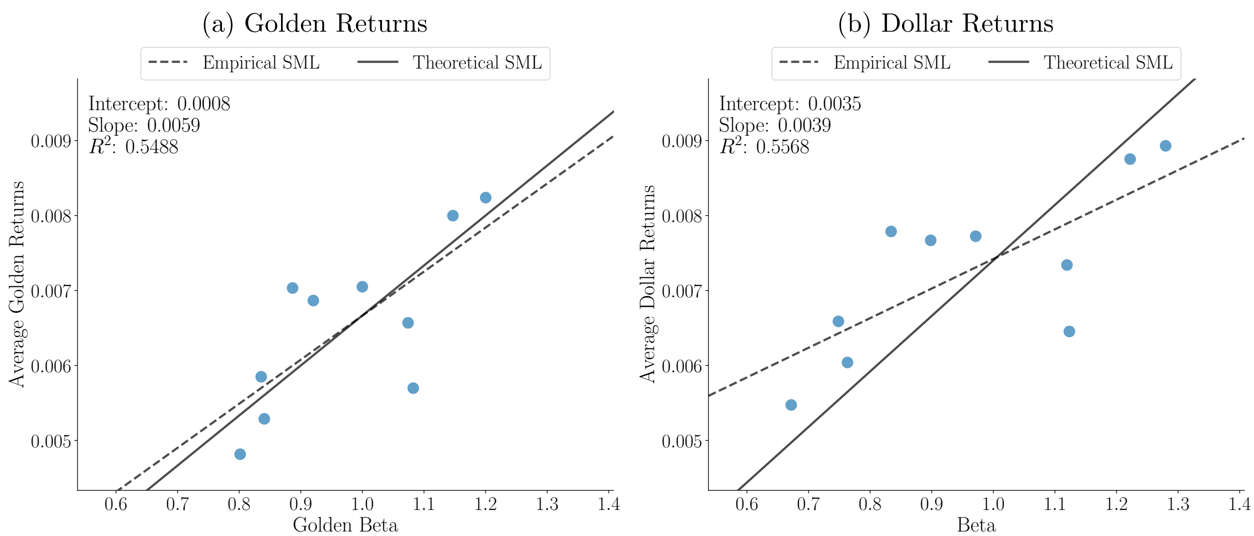

Figure A3: Average Monthly Returns versus Beta for Various Universes of Assets

This figure plots average monthly value-weighted dollar excess returns against market beta for the 20 beta-sorted portfolios. The data is from July 1927 to December 2024. Panel (a) shows the relationship between portfolios' average excess returns and beta for *all-but-microcap* stocks. Panel (b), (c), (d) and (e) shows the relationship for *all-but-short-lived*, *all-but-medium-lived*, *all-but-short-lived-microcap* and *all-but-medium-lived-microcap* stocks, respectively. The solid line represents the theoretical relation predicted by the CAPM, i.e, the theoretical Security Market Line (SML). The dashed line is the linear regression fit of the data, i.e., the empirical SML. We further report the estimated intercept, slope, and R^2 of the linear fit.

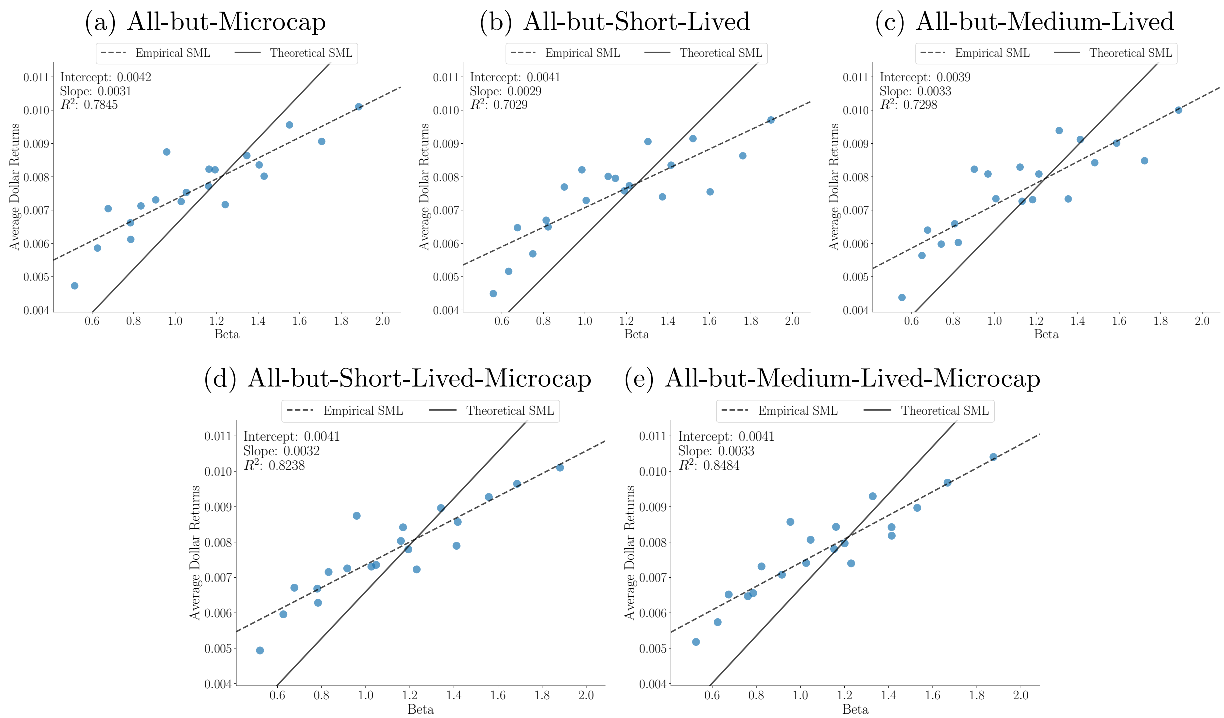

Table A1: Fama-MacBeth and Pooled Regressions for 25 Size- and Book-to-Market-Sorted Portfolios

This table presents estimates from Fama-MacBeth and pooled regressions of monthly value-weighted returns on betas for the 25 Fama and French size- and book-to-market-sorted portfolios. The data is from July 1927 to December 2024. Panel A shows results of monthly golden returns on betas. Panel B shows results of monthly dollar excess returns on betas. *t*-statistics are reported in parentheses. For the Fama-MacBeth regressions, they are calculated using the standard deviation of the time-series estimates. For the pooled regressions, they are calculated using clustered standard errors. ***, **, and * indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

Fama-MacBeth Regression			**Pooled Regression**		
Intercept (γ_0)	Beta (γ_1)	Average R^2	Intercept (α)	Beta (β)	R^2
Panel A: Golden Returns					
-0.0010	0.0079	0.1981	-0.0010	0.0079	0.0001
(-0.1876)	(1.3769)		(-0.1843)	(1.5264)	
Panel B: Dollar Returns					
0.0042	0.0037	0.2076	0.0042	0.0037	0.0001
(1.2755)	(1.0565)		(0.9721)	(0.9989)	

Table A2: Fama-MacBeth and Pooled Regressions for Ten Industry-Sorted Portfolios
This table presents estimates from Fama-MacBeth and pooled regressions of monthly value-weighted returns on betas for the ten industry-sorted portfolios. The data is from July 1927 to December 2024. Panel A shows results of monthly golden returns on betas. Panel B shows results of monthly dollar excess returns on betas. t-statistics are reported in parentheses. For the Fama-MacBeth regressions, they are calculated using the standard deviation of the time-series estimates. For the pooled regressions, they are calculated using clustered standard errors. ***, **, and * indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

Fama-MacBeth Regression			**Pooled Regression**		
Intercept (γ_0)	Beta (γ_1)	Average R^2	Intercept (α)	Beta (β)	R^2
Panel A: Golden Returns					
0.0009	0.0057	0.2153	0.0009	0.0057***	0.0001
(0.2833)	(1.5351)		(0.6454)	(3.9719)	
Panel B: Dollar Returns					
0.0035*	0.0038	0.2132	0.0035***	0.0038***	0.0002
(1.9073)	(1.5750)		(3.8816)	(4.0175)	

Table A3: Summary Statistics for Various Test Portfolios

This table presents summary statistics for the 25 Fama and French size- and book-to-market-sorted portfolios, and the ten industry-sorted portfolios. The data is from July 1927 to December 2024. Panel A reports the portfolio unconditional betas for the 25 size- and book-to-market-sorted portfolios obtained using golden returns ($\hat{\beta}^{\mathbf{g}}$) and dollar returns ($\hat{\beta}$). We further report portfolio average monthly returns ($\bar{R}^{\mathbf{g}}, \bar{R}$) and their volatility, defined as the standard deviation of realized returns (std($R^{\mathbf{g}}$), std(R)). t-statistics are reported in parenthesis. Panel B reports the summary statistics for the ten industry-sorted portfolios.

Panel A: 25 Size- and Book-to-Market-Sorted Portfolios

	ME1-BM1	ME1-BM2	ME1-BM3	ME1-BM4	ME1-BM5	ME2-BM1	ME2-BM2	ME2-BM3	ME2-BM4	ME2-BM5	ME3-BM1	ME3-BM2	ME3-BM3	ME3-BM4	ME3-BM5
$\hat{\beta}^{\mathbf{g}}$	1.2968	1.2540	1.2241	1.1667	1.2279	1.1704	1.1478	1.1297	1.1439	1.2349	1.1437	1.0884	1.0794	1.1168	1.2343
$\bar{R}^{\mathbf{g}}$	0.0042	0.0059	0.0091	0.0105	0.0125	0.0057	0.0086	0.0088	0.0097	0.0113	0.0064	0.0083	0.0085	0.0091	0.0101
std ($R^{\mathbf{g}}$)	0.1204	0.1034	0.0956	0.0905	0.0988	0.0880	0.0836	0.0814	0.0835	0.0937	0.0816	0.0752	0.0750	0.0793	0.0919
$\bar{\alpha}^{\mathbf{g}}$	-0.0036	-0.0017	0.0017	0.0034**	0.0050***	-0.0014	0.0016	0.0019*	0.0028**	0.0038**	-0.0005	0.0017**	0.0019**	0.0024**	0.0026*
t-stat ($\alpha^{\mathbf{g}}$)	(-1.5438)	(-0.9227)	(1.0547)	(2.2617)	(2.8974)	(-1.1447)	(1.5579)	(1.8120)	(2.2385)	(2.5973)	(-0.5442)	(2.3703)	(2.3858)	(2.3723)	(1.9231)
$\hat{\beta}$	1.5998	1.3958	1.3602	1.2655	1.3611	1.2715	1.2326	1.2003	1.2162	1.3769	1.2465	1.1316	1.1215	1.1721	1.3573
$\bar{R}$	0.0081	0.0094	0.0126	0.0140	0.0160	0.0091	0.0121	0.0123	0.0132	0.0148	0.0099	0.0118	0.0119	0.0126	0.0136
std (R)	0.1196	0.0969	0.0888	0.0830	0.0920	0.0800	0.0750	0.0724	0.0746	0.0870	0.0738	0.0650	0.0649	0.0696	0.084
$\bar{\alpha}$	-0.0055**	-0.0028	0.0006	0.0027*	0.0041**	-0.0022*	0.0010	0.0014	0.0022*	0.0028*	-0.0013	0.0013*	0.0016**	0.0019*	0.0016
t-stat(α)	(-2.4704)	(-1.5630)	(0.4281)	(1.8135)	(2.4175)	(-1.8350)	(0.9815)	(1.3263)	(1.7959)	(1.9415)	(-1.3467)	(1.8930)	(1.9917)	(1.9424)	(1.2445)

	ME4-BM1	ME4-BM2	ME4-BM3	ME4-BM4	ME4-BM5	ME5-BM1	ME5-BM2	ME5-BM3	ME5-BM4	ME5-BM5
$\hat{\beta}^{\mathbf{g}}$	1.0559	1.0593	1.0663	1.1127	1.2576	0.9810	0.9639	0.9823	1.0735	1.2126
$\bar{R}^{\mathbf{g}}$	0.0065	0.0070	0.0077	0.0089	0.0093	0.0061	0.0056	0.0063	0.0058	0.0088
std ($R^{\mathbf{g}}$)	0.0726	0.0719	0.0735	0.0784	0.0936	0.0660	0.0649	0.0677	0.0761	0.0935
$\bar{\alpha}^{\mathbf{g}}$	0.0001	0.0006	0.0012*	0.0021**	0.0016	0.0002	-0.0003	0.0004	-0.0007	0.0015
t-stat ($\alpha^{\mathbf{g}}$)	(0.1416)	(0.9140)	(1.6486)	(2.2222)	(1.1149)	(0.3388)	(-0.6110)	(0.5553)	(-0.7321)	(0.9349)
$\hat{\beta}$	1.0888	1.0914	1.1049	1.1616	1.3930	0.9609	0.9450	0.9692	1.0994	1.3006
$\bar{R}$	0.0100	0.0105	0.0112	0.0123	0.0127	0.0095	0.0090	0.0098	0.0092	0.0122
std (R)	0.0621	0.0612	0.0633	0.0684	0.0860	0.0535	0.0527	0.0560	0.0656	0.0849
$\bar{\alpha}$	-0.0002	0.0003	0.0009	0.0017*	0.0006	0.0003	-0.0001	0.0005	-0.0009	0.0007
t-stat (α)	(-0.2357)	(0.5143)	(1.2805)	(1.7888)	(0.3913)	(0.5701)	(-0.2657)	(0.7014)	(-0.9928)	(0.4383)

Panel B: 10 Industry-Sorted Portfolios

	Telcm	NoDur	Utils	Hlth	Enrgy	Shops	Manuf	Other	HiTec	Durbl
$\hat{\beta}^{\mathbf{g}}$	0.8016	0.8357	0.8408	0.8867	0.9204	0.9999	1.0741	1.0825	1.1470	1.2002
$\bar{R}^{\mathbf{g}}$	0.0048	0.0058	0.0053	0.0070	0.0069	0.0071	0.0066	0.0057	0.0080	0.0082
std ($R^{\mathbf{g}}$)	0.0615	0.0596	0.0664	0.0669	0.0739	0.0706	0.0726	0.0744	0.0810	0.0909
$\bar{\alpha}^{\mathbf{g}}$	-0.0000	0.0008	0.0002	0.0017*	0.0013	0.0010	0.0001	-0.0009	0.0010	0.0010
t-stat ($\alpha^{\mathbf{g}}$)	(-0.0472)	(0.9865)	(0.1665)	(1.6819)	(0.9844)	(1.1794)	(0.0916)	(-1.2722)	(1.1228)	(0.6788)
$\hat{\beta}$	0.6718	0.7485	0.7632	0.8341	0.8983	0.9714	1.1195	1.1234	1.2221	1.2797
$\bar{R}$	0.0082	0.0093	0.0087	0.0105	0.0104	0.0104	0.0100	0.0091	0.0114	0.0116
std (R)	0.0468	0.0458	0.0547	0.0554	0.0643	0.0582	0.0623	0.0642	0.0717	0.0819
$\bar{\alpha}$	0.0009	0.0015**	0.0008	0.0021**	0.0015	0.0011	-0.0003	-0.0012*	0.0004	0.0002
t-stat (α)	(1.0052)	(2.0570)	(0.7687)	(2.2067)	(1.1842)	(1.3184)	(-0.5222)	(-1.7882)	(0.4751)	(0.1501)

Table A4: Model Performance Summary, July 1963 to December 2024

This table tests the ability of CAPM , Fama-French three-factor model (*FF3*), and Carhart four-factor model (*FFC4*) to explain monthly (excess) returns on 20 beta-sorted portfolios (Panel A), 25 size- and book-to-market-sorted portfolios (Panel B), and ten industry-sorted portfolios (Panel C). The sample covers the period July 1963 to December 2024. For each set of 10, 20 or 25 regressions, the table reports the *GRS* statistic (*stat.*) and its p-value (p-val.) testing whether the expected values of intercept estimates are jointly equal to zero. We further report the average absolute intercepts ($A|\alpha_p|$), the average absolute intercepts to the average absolute portfolio returns ($\frac{A|\alpha_p|}{A|r_p|}$), and Hansen-Jagannathan distance (*HJ dist.*), which measures the model's pricing error.

	Gold-Denominated Returns					Dollar-Denominated Returns				
	GRS (stat.)	GRS (p-val.)	$A\|\alpha_p\|$	$\frac{A\|\alpha_p\|}{A\|r_p\|}$	HJ dist.	GRS (stat.)	GRS (p-val.)	$A\|\alpha_p\|$	$\frac{A\|\alpha_p\|}{A\|r_p\|}$	HJ dist.
Panel A: 20 Beta-Sorted Portfolios										
CAPM	1.0656	0.3818	0.0009	0.7324	0.1729	1.4743	0.0828	0.0015	1.7141	0.2045
FF3	1.3262	0.1539	0.0009	0.7371	0.1944	2.1111	0.0032	0.0014	1.5370	0.2470
FFC4	1.6924	0.0298	0.0015	1.1961	0.2234	1.7478	0.0226	0.0009	0.9936	0.2294
Panel B: 25 Size- and Book-to-Market-Sorted Portfolios										
CAPM	3.2780	0.0000	0.0019	1.2990	0.3402	4.1216	0.0000	0.0019	1.3196	0.3837
FF3	2.8456	0.0000	0.0008	0.5891	0.3195	3.6157	0.0000	0.0009	0.6488	0.3627
FFC4	2.4732	0.0001	0.0008	0.5387	0.3030	3.1365	0.0000	0.0009	0.6003	0.3449
Panel C: Ten Industry-Sorted Portfolios										
CAPM	0.9940	0.4469	0.0007	0.9672	0.1172	1.4202	0.1666	0.0010	1.2732	0.1410
FF3	2.4113	0.0080	0.0012	1.6272	0.1841	3.3082	0.0003	0.0014	1.8235	0.2171
FFC4	2.3803	0.0089	0.0013	1.7446	0.1861	3.0542	0.0008	0.0012	1.6513	0.2130

Table A5: Fama-MacBeth and Pooled Regressions for Expanded Unconditional Betas

This table presents estimates from Fama-MacBeth and pooled regressions of monthly value-weighted dollar excess returns on betas for 20 beta-sorted portfolios. Portfolios unconditional betas are computed each month, requiring at least 36 months of past returns. The data is from July 1930 to December 2024. t-statistics are reported in parentheses. For the Fama-MacBeth regressions, they are calculated using the standard deviation of the time-series estimates. For the pooled regressions, they are calculated using clustered standard errors. ***, **, and * indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

Fama-MacBeth Regression			Pooled Regression		
Intercept (γ_0)	Beta (γ_1)	Average R^2	Intercept (α)	Beta (β)	R^2
0.0040***	0.0029	0.3663	0.0031***	0.0036***	0.0004
(2.8477)	(1.3957)		(6.4706)	(8.3519)	

Table A6: Fama-MacBeth and Pooled Regressions for Various Universes of Assets

This table presents estimates from Fama-MacBeth and pooled regressions of monthly value-weighted dollar excess returns on betas for the 20 beta-sorted portfolios. The data is from July 1927 to December 2024. Panel A shows results for *all-but-microcap* stocks. Panel B, C, D, and E shows results for *all-but-short-lived*, *all-but-medium-lived*, *all-but-short-lived-microcap*, and for *all-but-medium-lived-microcap* stocks, respectively. t-statistics are reported in parentheses. For the Fama-MacBeth regressions, they are calculated using the standard deviation of the time-series estimates. For the pooled regressions, they are calculated using clustered standard errors. ***, **, and * indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

Fama-MacBeth Regression			**Pooled Regression**		
Intercept (γ_0)	Beta (γ_1)	Average R^2	Intercept (α)	Beta (β)	R^2
Panel A: All-but-Microcap					
0.0042***	0.0031	0.3612	0.0042***	0.0031***	0.0003
(3.0606)	(1.5062)		(8.8066)	(8.4882)	
Panel B: All-but-Short-Lived					
0.0041***	0.0029	0.3677	0.0041***	0.0029***	0.0002
(3.0353)	(1.4254)		(7.4193)	(6.4615)	
Panel C: All-but-Medium-Lived					
0.0039***	0.0032	0.3659	0.0039***	0.0032***	0.0003
(2.8027)	(1.5813)		(7.0081)	(7.3481)	
Panel D: All-but-Short-Lived-Microcap					
0.0041***	0.0032	0.3602	0.0041***	0.0032***	0.0003
(3.0113)	(1.5649)		(10.8367)	(11.1994)	
Panel E: All-but-Medium-Lived-Microcap					
0.0040***	0.0033	0.3557	0.0040***	0.0033***	0.0003
(2.9575)	(1.6270)		(12.5191)	(13.2932)	