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Cash-Hedged Stock Returns*

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Abstract

Corporate cash piles vary across companies and over time. A firm's cash holding is an implicit position in a low-return asset that is correlated across firms. Cash generates variation in beta estimates. We show how investors can hedge out the cash on firms' balance sheets when making portfolio choices. We decompose stock betas into components that depend on the firm's cash holding, return on cash, and cash-hedged return. Common asset pricing premia—size, value, and momentum—have large implicit cash positions. Portfolios of cash-hedged premia often have higher Sharpe ratios because firms' cash returns are correlated.

JEL Codes: G12

Keywords: cross-section of expected returns, cash, risk factor, size, value, momentum

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> [We] believe in operating with many redundant layers of liquidity, and we avoid any sort of obligation that could drain our cash in a material way. That reduces our returns in 99 years out of 100. But we will survive in the 100^{th} while many others fail. And we will sleep well in all 100.
>
> Warren E. Buffett (Berkshire Hathaway Shareholder Letter, 2012)

1 Introduction

Cash is necessary for companies' operations. Firms use cash to make payments, finance investments, and manage risk. But holding cash comes at a cost: its low pecuniary return. We study the effect of corporate cash holdings on stock returns and their effect on betas. We show how investors can explicitly account for the effect of corporate cash holdings in their portfolio decision. When an investor owns stock in a company with substantial cash, the investor has an implicit cash position managed by the company—something the investor might not intend.

Cash is an economically significant source of time-series and cross-sectional variation in public firms' assets. The value-weighted U.S. stock market held 22% of its assets in cash and short-term equivalents in December 2020 compared to 8% in the 1980s. An investor buying the market in 2020 ends up with an implicit cash position three times larger than an investor buying the market in 1980. The variation across individual firms' cash, as a percent of total assets, has increased almost every decade since the 1970s, with a peak during the dot-com bubble.

We argue two related points. First, the value of corporate cash is distinct and separable from the value of the firm's primary business. Second, firms' cash returns are correlated. When investors hedge out the correlated cash returns, the resulting cash-hedged returns are less correlated, yielding portfolios that provide better diversification.

Cash held by a company is not the same as cash held by an investor. Companies have good reasons to hold extra cash to support their business: as part of precautionary savings or because internal financing is cheaper than external financing, for example. Companies may also be good at investing cash, earning higher returns on their cash portfolios. Investors should manage their implicit cash positions explicitly, regardless of why the company holds cash.

Investors can hedge their implicit cash positions in three steps. First, we decompose a company's stock return into its cash and non-cash components. Second, we use the decomposed return to compare a company's standard—that is, not cash-hedged—beta with its cash-hedged beta. Third, we show that controlling for the cash bias in standard betas provides investors with a richer covariance structure across stocks, which allows them to create relatively more risk-efficient portfolios.

We calculate cash-hedged returns by treating a stock as a portfolio of two securities: a cash security and a non-cash security. The firm's cash share—the share of assets held in cash—pins down the portfolio's relative weight on the two securities. We can use this known cash share and the stock return to back out the non-cash return once we estimate the firm-specific cash return. As a simple example: suppose a company held half its assets in cash that earns the risk-free rate. An investor with \$100 of the company's stock owns an indirect cash position of \$50. The investor can hedge this cash exposure by shorting the risk-free rate and using the proceeds to buy even more of the company's stock.

But a company's cash positions likely won't earn the risk-free rate because the value of cash inside firms depends on several factors: the company's prospects and management, the broader business cycle, and tax frictions, to name a few. We estimate firm-specific cash returns by building on Faulkender and Wang (2006)'s model of firm-specific marginal cash values. We find the equal-weighted average value of \$1.00 inside a firm is \$1.01 and has an average annual return of 0.8%. We back out a firm's cash-hedged stock return using our stock return decomposition and the firm's stock return, cash return, and cash share.

Companies' standard betas to asset pricing factors vary less than their non-cash return betas. Standard betas are attenuated around their mean because they reflect a combination of their non-cash return beta and cash return beta. Cash drags down standard beta estimates because most firms' cash returns are lower and less volatile and therefore have a lower covariance with the pricing factors. We decompose standard betas into their cash-hedged betas and an adjustment term under two pricing models: the capital asset pricing model (CAPM) and the Fama–French three-factor model. In both cases, the decomposition shows that cash-hedged betas vary substantially more than standard beta estimates.

We then take the beta decomposition to the data. Intuitively, our cash-hedged beta estimates reflect the covariance of a stock with pricing factors after removing the confounding effect of cash. Because many firms' cash returns are correlated—and generally not too far from the risk-free rate—the covariances of firms' cash-hedged returns are less correlated. We examine the richer cash-hedged return covariances in three ways. First, we plot the securities market line to show that cash-hedged betas line up with expected returns better than standard betas. Second, the corresponding cross-sectional prices of risk estimates are significant. A one standard deviation increase in a firm's beta to the market factor increases the annualized expected risk premium by 3 percentage points (pp). Third, we show that the efficient frontier is steeper using cash-hedged portfolios, so the cash-hedged portfolios have a more efficient tangency portfolio with a higher Sharpe ratio.

We show that common empirical asset pricing factors—size, value, and momentum—have large and time-varying net cash positions. One concern is that cash hedging for factors requires unknowable contemporaneous knowledge about a firm's cash share. But we find that lagged accounting data is a simple and effective method to remove net cash positions from size, value, and momentum. A cash-hedging strategy effectively removes these net cash positions, and portfolios of the factors benefit from hedging cash.

During market turmoil, persistent biases in betas and covariances could prompt large losses if firms rapidly accumulate or deplete their cash. We study the Covid-19 pandemic to better understand the value of cash in times of stress. Firms increased their cash shares in 2020, and the value of a dollar inside the firm increased. The value-weighted average value of \$1 held on corporate balance sheets increased 3.6% between January 2020 and November 2020, increasing from \$1.08 to \$1.12. We find that firms hold cash despite having low firm-specific cash returns, and firms rebalance to hold more cash if their cash levels drop after a year of poor cash returns.

Related Literature We contribute to the literature that studies why U.S. firms have held an increasing amount of cash since the 1980s and its effect on firms' value. The literature has studied several mechanisms: precautionary savings motives given riskier cash flows (Opler et al., 1999; Acharya et al., 2007; Bates et al., 2009; Bolton et al., 2011; Acharya et al., 2012; Palazzo, 2012; Azar et al., 2016; Begenau and Palazzo, 2021); agency costs reflecting differences in the interests of managers and shareholders (Jensen and Meckling, 1976; Jensen, 1986; Richardson, 2006; Dittmar and Mahrt-Smith, 2007; Nikolov and Whited, 2014); taxes (Foley et al., 2007); changes in innovation, research and development, and intangible capital (Brown and Petersen, 2011; Falato and Sim, 2014; He and Wintoki, 2016; Lyandres and

Palazzo, 2016; Gao, 2018; Zhao, 2020; Falato et al., 2020); financing transaction costs (Miller and Orr, 1966; Huberman, 1984); and, information asymmetry (Myers and Majluf, 1984). Our paper differs from the literature in that we focus on the effects of those cash holdings on asset pricing betas and factors. Our paper estimates cash and non-cash returns for several established risk factors—market, size, value—and studies the cross-sectional properties of the factors' cash and non-cash returns.

2 Decomposing Stock Returns

We assume a firm's stock, with return r_t^i for firm i in month t, is a portfolio of two assets: a cash and non-cash asset. The firm's cash earns monthly return b_t^i. We assume cash returns are firm-specific due to the empirical and theoretical evidence indicating many factors generate variation in the value of cash across firms. The firm's non-cash assets include all the firm's assets except for the firm's cash and has monthly return e_t^i, which we call the *cash-hedged stock return*, as opposed to r_t^i which we will call the firm's *standard stock return*.

Splitting each stock into the two disjoint assets lets us equate a stock's return to the weighted average of the cash return and the cash-hedged return. We assume the weight of the cash asset, w_t^i, is the ratio of a firm's cash to total assets so that:

$$\begin{aligned} r_t^i &= \left(\frac{\text{Non-Cash Assets}_t^i}{\text{Total Assets}_t^i}\right)\text{Return}_t^{i,\text{cash-hedged}} + \left(\frac{\text{Cash}_t^i}{\text{Total Assets}_t^i}\right)\text{Return}_t^{i,\text{cash}} \\ &= (1-w_t^i)e_t^i + w_t^i b_t^i. \end{aligned} \tag{1}$$

Equation 1 is an accounting identity equating a portfolio's return to the returns of the portfolio's components. The unknown cash-hedged return e_t^i is

$$e_t^i = \frac{1}{(1-w_t^i)}r_t^i - \frac{w_t^i}{(1-w_t^i)}b_t^i. \tag{2}$$

Equation 2 frames the cash-hedged return e_t^i as the return of a particular portfolio constructed with two hypothetical trades. The first trade buys $1/(1-w_t^i)$ shares of the firm's stock. The first trade uses leverage to purchase the stock because the fraction of a firm's total assets held in cash is between zero and one. The second trade sells exactly the amount of firm cash, $w_t^i/(1-w_t^i)$, underlying the portfolio's $1/(1-w_t^i)$ units of the firm's stock.

The portfolio's two trades leave the portfolio with net-zero units of the firm's cash and one unit of the firm's non-cash assets. The equation's description as a portfolio with two trades is hypothetical because firms' cash and non-cash assets cannot be individually bought and sold. Our empirical approach, discussed later, will relax some assumptions to make a cash-hedged strategy implementable by using lagged cash weights and a model to estimate firm-specific cash returns b_t^i.

The challenge is that there are two unknowns in equation 2: e_t^i and b_t^i. We build on the marginal cash value model of Faulkender and Wang (2006) to estimate firm-specific cash returns, which we use to solve for e_t^i. We discuss the cash return estimation in section 4.

Individual cash-hedged stocks can be easily aggregated to value-weighted portfolios. We use the firm-level stock return decomposition to determine the cash and non-cash components of several value-weighted portfolios. The return of value-weighted stock portfolio r_t^p where member stocks have value weights v_t^i is

$$r_t^p = \sum_{i \in p} v_t^i r_t^i = \sum_{i \in p} v_t^i \left((1 - w_t^i) e_t^i + w_t^i b_t^i \right). \tag{3}$$

The value-weighted cash-hedged and cash-only portfolio returns—denoted e_t^p and b_t^p—measure a stock portfolio's aggregate cash-hedged and cash returns without cash-share changes contributing to the portfolios' returns. We define $\gamma_t^i = w_t^i(e_t^i - b_t^i)$ as the difference between a stock's non-cash and cash return, weighted by the stock's cash share. We use γ_t^i to decompose a stock's return:

$$r_t^i = e_t^i - w_t^i(e_t^i - b_t^i) = e_t^i - \gamma_t^i. \tag{4}$$

The equation is helpful for two reasons. First, we can interpret the equation's first term as the stock's return if the company kept no cash on its balance sheet; the second term is the cost that the company incurs by holding cash, which can be positive or negative, on its balance sheet instead of additional non-cash assets. Second, we can view the equation as the reorganization of a stock's cash and non-cash returns into one term containing variation in the stock's return due the firm's cash holdings (γ_t^i), and another term that does not (e_t^i) .

We also define a stock's excess return as $r_t^{i,xs} = r_t^i - r_t^f$, where r_t^f is the risk-free rate and define a stock's excess non-cash return as $e_t^{i,xs} = e_t^i - r_t^f$. We use these definitions to decompose a portfolio's excess return:

$$r_t^{p,xs} = \sum_{i \in p} \upsilon_t^i r_t^{i,xs} = e_t^{p,xs} - \gamma_t^p \tag{5}$$

Table A1 summarizes identities used to decompose stock and portfolio returns into cash and non-cash returns.

3 Data

Sample We use monthly stock return, price, and share data from the Center for Research in Security Prices (CRSP) and Compustat. We join CRSP and Compustat data with the CCM link table provided by Wharton Research Data Services. Our stock sample construction follows Faulkender and Wang (2006) and Asness et al. (2013). We describe the sample selection procedure in detail in section A.1.

We restrict the paper's stock sample to estimate firms' cash shares and non-cash returns. We require non-missing quarterly total assets and non-missing quarterly cash and short-term equivalent observations six months before the current month. We also require firms' quarterly total assets and quarterly cash and short-term equivalents variables to be greater than zero. These sample restrictions are necessary to construct the paper's cash share variable.

Our paper's sample begins in January 1978 and ends in December 2020. Both CRSP and Compustat provide data for years before 1976, but we do not include earlier years in our sample because the quarterly cash and total asset observations are missing for about 80% of the merged, monthly CRSP–Compustat sample before 1976.

Cash Variable We measure a firm's cash share, variable w_t^i in equation 1, as the ratio of cash and short-term investments to total assets, and we lag both variables by six months to ensure the accounting variable is in investors' information set. We chose a six-month lag for the cash share to be consistent with the construction of the book-to-market variable. A six-month lag also makes the variables' information relatively recent without using financial information before it's available to investors.

A stock's cash share in month t is an unobserved variable but a firm's lagged cash to total asset ratio is a reasonable proxy for a stock's cash share. We later report results supporting our assumption that lagged cash shares proxy for current cash shares.

GAAP defines our cash variable—cash and short-term investments—as "cash and all securities readily transferable to cash ...." The variable includes investment in short-term money-market funds; we provide the full definition in the online appendix.

We use this line-item instead of pure cash for three reasons. First, the cash item is considerably sparser in the accounting data. Second, the short-term investments included in the item are all investments that we expect have returns not far from the risk-free rate. And third, corporate treasurers do not hold their entire liquidity needs in cash in practice —the current FDIC insurance limit is $250,000—but routinely use money-market instruments like highly-rated commercial paper and money-funds as cash-like stores of value.

We plot the aggregate market cash share in the left panel of Figure 1. The cash share ranges from 6% to 24% between the 1978 and 2020 and has a well-documented upward trend beginning in the 1980s with a spike to the highest levels during the Covid pandemic. The right panel of the figure shows the cross-sectional standard deviation across firm's cash shares in each period. There is a growing spread of cash shares across firms until the dot-com bubble, and the standard deviation has hovered around the same level since the 2008 financial crisis with a weak upward trend.

Size, Value, and Momentum Variables We use the variable definitions from Asness et al. (2013) to calculate firms' book-to-market and momentum. A stock's book-to-market ratio (BEME) at the beginning of the month is $\text{Book Value}^i_{t-6}/\text{Market Value}^i_{t-1}$. Asness et al. (2013) use this definition because it is a standard, conservative, and easily implemented definition of BEME. The paper's results are similar when using the BEME and market value definitions from Fama and French (1992) which uses more complex lags.

We compute firm size as the product of a firm's shares outstanding and share price at the beginning of the current month. We define momentum as a stock's gross return from the beginning of month $t-12$ to the end of month $t-2$ (Jegadeesh and Titman, 1993; Asness, 1994; Grinblatt and Moskowitz, 2004). Our momentum definition is standard, including our omission of a stock's return over month $t-1$.

Portfolios Gathering stocks in portfolios sorted on a characteristic is a standard procedure for constructing dependent variables for cross-sectional asset pricing tests. All the portfolios we construct use monthly returns, use value-weights, and are rebalanced monthly. Stocks' value weights are determined monthly by their beginning of month market capitalizations.

We construct two sets of 25 size and book-to-market portfolios, which we will use as test assets in our cross-sectional regressions. First, we construct 25 size and book-to-market portfolios like Fama and French (1992). We independently double sort stocks on size and book-to-market, each into five groups. By intersecting these groups, we assign stocks to one of 25 portfolio groups. We then calculate the value-weighted portfolio returns for each of these 25 portfolio groups. These are the standard 5×5 size and book-to-market portfolios in standard return terms.

Second, we construct 25 cash-hedged portfolio returns. We use the same methodology to assign stocks to portfolios, but we calculate the returns using each firm's cash-hedged returns rather than the firm's standard stock return to calculate the value-weighted returns. We describe our cash return estimation in detail later in Section 4. Table 1 shows the equal-weighted cash share and standard and cash-hedged return statistics for 25 size and book-to-market portfolios. We follow an analogous procedure to form 10 momentum-sorted portfolios.

Factors We use two approaches to construct factors: the first uses only the sorting variable in a single sort, and the second uses double sorts. Each approach results in self-financing long-short factors. All the factors use monthly returns, use value-weights, and are rebalanced monthly. Stocks' value weights are determined monthly by their beginning of month market capitalizations. We create the factors in both standard and cash-hedged return terms.

First, we create simple factors: based on only the sorting variable, we single sort our data into three equal-sized groups, and then we calculate the three value-weighted portfolios—High (P3), Middle (P2) and Low (P1). We calculate each strategy's premium as P3−P1. For example, the value premium is the difference between the return of the high book-to-market portfolio less the return of the low book-to-market portfolio. We construct three simple factors: *Value*, *Size*, and *Mom* and calculate the standard returns and cash-hedged returns to each trading strategy. The factors are constructed using sorts of book-to-market, book value, and past returns as discussed in section 3.

Second, we construct *HML*, *SMB*, and *MOM* using double sorts. Double sorting helps control for the confounding effect that sorting on one variable might also implicitly sort on another. For example, high and low value stocks may consistently coincide with higher and lower returns because sorting on value implicitly sorts on size. *SMB* and *HML* are constructed using a strategy like Fama and French (1993) except we use three size terciles rather than two. We use the same method to construct *MOM* with sorts on size and past returns. In this way, all three factors control for size.

4 Estimating Firm-Specific Cash Returns

We estimate the return on firms' cash in four steps. First, we use the methodology from Faulkender and Wang (2006) to estimate the marginal cash value for each firm. Second, we estimate the firm's average cash value by integrating over the marginal values for a firm's cash. Third, we compute the return on a firm's cash by dividing the value of a firm's cash at fiscal year-end by the value of a firm's cash at the previous fiscal year-end. Fourth, we create firm-specific cash return mimicking portfolios to estimate cash returns at a higher, monthly, frequency.

We follow Faulkender and Wang (2006) to calculate each firm's marginal value of cash. The dependent variable is a stock's excess return over fiscal year t less the return of a benchmark portfolio over the same period. The benchmark portfolio controls for a stock's expected return associated with the stock's size and book-to-market ratio. The regression's independent variables are firm characteristics that could fluctuate alongside the firm's cash. The independent variables are scaled by the firm's market equity at the beginning of the fiscal year, M^i_{t-1}.

Since both the dependent and independent variables are scaled by a stock's beginning-of-fiscal-year market equity, the regression coefficient measures the dollar change in shareholder value when the firm's cash changes by one dollar. The regression specification from Faulkender and Wang (2006) is

$$\begin{aligned} r^i_t - R^{i,B}_t = \gamma_0 &+ \gamma_1 \frac{\Delta C^i_t}{M^i_{t-1}} + \gamma_2 \frac{\Delta E^i_t}{M^i_{t-1}} + \gamma_3 \frac{\Delta NA^i_t}{M^i_{t-1}} + \gamma_4 \frac{\Delta RD^i_t}{M^i_{t-1}} \\ &+ \gamma_5 \frac{\Delta I^i_t}{M^i_{t-1}} + \gamma_6 \frac{\Delta D^i_t}{M^i_{t-1}} + \gamma_7 \frac{C^i_{t-1}}{M^i_{t-1}} + \gamma_8 L^i_t + \gamma_9 \frac{NF^i_t}{M^i_{t-1}} \\ &+ \gamma_{10} \frac{C^i_{t-1}}{M^i_{t-1}} \times \frac{\Delta C^i_t}{M^i_{t-1}} + \gamma_{11} L^i_t \times \frac{\Delta C^i_t}{M^i_{t-1}} + \varepsilon^i_t. \end{aligned} \tag{6}$$

The return of stock i over fiscal year t is r_t^i, and $R_t^{i,B}$ is the fiscal year return for one of the 5×5 size and book-to-market portfolios available on Kenneth French's website. The portfolios' fiscal year returns are computed from the portfolios' monthly returns over each firm's fiscal year. The stock's size and BEME quintiles determine which of the 25 value-weighted size and BEME portfolios $R_t^{i,B}$ represents. We provide details on the breakpoints we use in the online appendix.

In the regression, ΔX_t^i denotes the value $X_t^i - X_{t-1}^i$ which proxies for unexpected changes in the variable. C_t^i is cash and short-term equivalents. I_t^i is interest expense. D_t^i is common dividends paid. L_t^i is market leverage at the end of fiscal year t and equals total debt divided by total debt plus market equity. NF_t^i is net financing and equals total equity issuance minus repurchases plus debt issuance minus debt redemptions. RD_t^i is research and development expense. E_t^i is earnings before extraordinary items plus deferred tax credits and investment tax credits. NA_t^i is net assets and equals total assets minus cash holdings. Last, M_{t-1}^i is the market value of equity at the end of the previous year. Earnings, net assets, research and development expense, interest expense, dividends paid, and net financing are variables controlling for correlation between cash and returns and unobserved variables that affect stock returns. Table A2 reports regression coefficients for the Faulkender and Wang (2006) regression specification. Our regression results are similar to the Faulkender and Wang (2006) results.

Taking the partial derivative of equation 6 with respect to ΔC_t^i yields the marginal value of \$1 to firm i at time t, and plugging in the coefficients estimated in Table A2 gives:

$$\begin{aligned}\text{Marginal Cash Value}_t^i &= \gamma_1 + \gamma_{10}\frac{C_{t-1}^i}{M_{t-1}^i} + \gamma_{11} L_t^i \\ &= 1.285 + \left(-0.789 \times \frac{C_{t-1}^i}{M_{t-1}^i}\right) + \left(-1.061 \times L_t^i\right).\end{aligned}$$

The equal-weighted average marginal cash value across all firms is $1.285 + (-0.789 \times 0.162) + (-1.061 \times 0.201) = \$0.94$.

We then compute the average value of a firm's cash by integrating the marginal dollar value equation with respect to the firm's cash at the beginning of the year, then dividing by the firm's cash at the beginning of the year. We assume the value of zero dollars to the shareholder is zero, as the value of the first dollar would likely go toward expenses or debtors rather than the shareholders:

$$\begin{aligned}\text{Average Cash Value}_t^i &= \frac{1}{C_{t-1}^i}\int_0^{C_{t-1}^i} \text{Marginal Cash Value}_t^i \, dC_{t-1}^i \\ &= 1.285 + \left(-0.789 \times \frac{1}{2} \times \frac{C_{t-1}^i}{M_{t-1}^i}\right) + \left(-1.061 \times L_t^i\right)\end{aligned}$$

The equal-weighted average cash value across all firms is $1.285 + (-0.789 \times 0.5 \times 0.162) + (-1.061 \times 0.201) = \$1.01$. Figure 2 shows the value of \$1 for the market portfolio. In the last two decades, the value-weighted value of \$1 in a firm is greater than 1, and the value of cash has varied substantially across firms.

We use a firm's average cash value estimates to compute the annual return on a firm's cash by dividing the current fiscal year-end average cash value by the previous fiscal year-end average cash value:

$$\text{Fiscal year cash return}_{i,t} = \frac{\text{Average Cash Value}_t^i}{\text{Average Cash Value}_{t-1}^i}. \tag{7}$$

We compute a firm's monthly cash return over a fiscal year t by forming firm-specific cash return mimicking portfolios in the spirit of Adrian et al. (2014). We form the mimicking portfolios by regressing a firm's cash returns on returns for one-month and one-year Treasuries using annual data and risk factors for unexpected changes in interest rates (*TERM*) and default (*DEF*). We define *TERM* and *DEF* analogous to Fama and French (1993), but we calculate the variables using securities with less than one-year maturity to reflect the term structure and default risk faced by corporate treasurers managing their cash and short-term equivalent portfolios. *TERM* is the difference between the one-year Treasury bill return and the one-month Treasury bill rate. *DEF* is the difference between highly-rated three-month commercial paper return and one-month Treasury bill return.[1] We then estimate a firm's monthly cash returns with the mimicking portfolio weights.

Finally, we estimate cash-hedged returns e_t^i using Equation 2. We winsorize both yearly and monthly e_t^i estimates at the 1% and 99% levels to reduce the influence of outliers.

Figure 3 plots the value-weighted return to cash and the risk-free rate of return. On

[1] The three-month commercial paper series splices together three-month bankers' acceptances, available before 1997, and AA nonfinancial commercial paper, available beginning in 1997. We convert the monthly yield series into a total return index using CP Return $\text{Index}_t = (1 + y_{t-2}^{3m}/100 \times (1/12)) \times$ CP Return Index_{t-1}.

average, the value-weighted cash return is smaller than the risk-free return, but cash returns have a much larger variance. The average monthly risk-free return is 0.34% over our sample with a standard deviation of 0.2%. The average monthly value-weighted cash return is 0.06% with a standard deviation of 1.6%.

5 Empirical Results

We have five results: first, we show that cash returns are correlated across firms, making correlations of standard returns artificially higher. Second, we decompose factor betas to show the effect of cash returns on betas and expected returns. Third, the cross-sectional price of risk is positive and significant when using cash-hedged returns and factors. Fourth, we show that common empirical asset pricing factors—size, value, and momentum—have large and time-varying net cash positions. Fifth, we show that cash returns increased dramatically during the Covid-19 pandemic.

5.1 Cash Returns and Correlation

First, we show that standard return factors have a common component: cash. We show that cash returns are correlated across firms. We randomly select two firms in our sample and calculate the correlation of their annual returns, and we repeat the process 100,000 times. In Table 2 we regress the 100,000 correlation coefficients on a constant to test whether they are positively correlated and to what degree they are correlated. The table shows the correlation of cash returns b_t^i, standard stock returns r_t^i, and cash-hedged returns e_t^i using this process. On average, firms' cash returns b_t^i are significantly positively correlated. As a result, firms' standard stock returns r_t^i are more correlated than firms' cash-hedged returns e_t^i. Cash-hedging removes this correlated component of returns and accounts for factors having time-varying cash shares.

5.2 Cash-Hedged Betas

Cash-hedged betas are different from standard betas. Cash holdings affect both betas and expected returns. The expected positive slope between betas and expected returns is clearer after cash-hedging and using cash-hedged returns produces betas with more heterogeneity across size and book-to-market portfolios. We show this holds for the standard CAPM model and a multifactor model.

Decomposing Betas We can decompose the standard CAPM into the cash-hedged beta, scaled by the ratio between the variance of the market-level excess cash-hedged return and the variance of the market-level standard return, plus an adjustment term:

$$\begin{aligned} \underbrace{\beta^{p,standard}}_{\text{standard stock beta}} &= \frac{Cov(r_t^{p,xs}, r_t^{m,xs})}{Var(r_t^{m,xs})} \\ &= \underbrace{\left(\frac{Cov(e_t^{p,xs}, e_t^{m,xs})}{Var(e_t^{m,xs})}\right)}_{\substack{\text{cash-hedged beta} \\ =\beta^{p,cash-hedged}}} \underbrace{\left(\frac{Var(e_t^{m,xs})}{Var(r_t^{m,xs})}\right)}_{\text{ratio of variances}} \\ &\quad + \underbrace{\frac{-Cov(\gamma_t^p, e_t^{m,xs}) - Cov(e_t^{p,xs}, \gamma_t^m) + Cov(\gamma_t^p, \gamma_t^m)}{Var(r_t^{m,xs})}}_{\text{adjustment term}} \end{aligned} \tag{8}$$

where $r_t^{p,xs}$ is the excess returns of each portfolio and $r_t^{m,xs}$ is the market-level excess standard stock return from section 2. If all companies held no cash, then $\gamma_t^i = 0$ and the adjustment term would be equal to zero and the ratio of the variances would be equal to 1. Then the market beta and the cash-hedged beta would be equivalent, and the standard return and cash-hedged return would also be equal.

Table 3 shows the beta decomposition for the 25 size and book-to-market portfolios. The ratio of the variances is roughly 1.4, so the cash-hedged market return is about 40% more volatile than the standard market return. On average, the cash-hedged and standard betas are similar, but betas differ depending on the portfolio's book-to-market. Growth portfolios, made of low-BEME stocks, have higher cash shares and a large difference between the standard and cash-hedged betas. Across all portfolios, the adjustment term is negative; but within a size bucket, growth portfolios have the most negative adjustment term. This variation translates to larger cash-hedged betas than standard betas for growth portfolios.

We can also relate standard betas from a multifactor model to cash-hedged betas using the Frisch-Waugh-Lovell Theorem, which we show in Appendix A.3. Tables A3 to A5 provide decomposed standard betas the market, size, and value from the Fama–French three-factor model.

Comparing Betas A basic test for an asset pricing model is whether the betas line up with expected returns to form a positively-sloped securities market line (SML). We calculate the standard market beta for the 25 size and book-to-market portfolios by regressing the standard returns on the standard market factor. We separately calculate the cash-hedged beta by regressing cash-hedged portfolio returns on the cash-hedged market factor. Figure 4 shows the SML of average returns against market betas. For standard returns, the SML is flatter, and the betas and expected returns fail to line up linearly with a positively-sloped line. The flat SML challenges the CAPM's validity for standard returns and is consistent with the existing literature.

There is a stronger linear relationship between average cash-hedged betas and expected cash-hedged returns for cash-hedged returns. The slope is 1.3, so increasing beta by a whole unit increases expected cash-hedged returns 1.3pp. Contrast this with the standard CAPM SML slope of 0.4, roughly two-thirds smaller. CAPM holds that the only measure of risk that is relevant for pricing securities is covariance with the market. Using cash-hedged returns provides a better description of the returns when using only a single factor.

We can also directly compare standard and cash-hedged betas. Figure 5 shows the cash-hedged and standard betas for the portfolios and the difference between the two. Portfolios with the largest and smallest value within a size bucket have the biggest difference between $\beta^{standard}$ and $\beta^{cash\text{-}hedged}$. Moving from growth to value in each size bucket corresponds to a switch from $\beta^{standard} < \beta^{cash\text{-}hedged}$ to $\beta^{standard} > \beta^{cash\text{-}hedged}$. In this view, standard betas are attenuated around their means, so cash-hedged betas have more variation.

The most extreme value portfolios have the largest discrepancy because there is a strong covariance between cash share and value. Growth stocks have a high cash share relative to value stocks, and growth stocks have the greatest difference between their standard and cash-hedged beta. Appendix A.4 discusses the correlation between cash and book-to-market in detail. Combined, the results indicate that cash shares lead to less heterogeneity in standard market betas.

Multivariate Betas While we have so far focused on CAPM, we now expand the results to multifactor models. We use the standard Fama–French three-factor model to show how betas and expected returns line up and compare standard and cash-hedged betas. Figure 6 plots the securities market line of portfolio returns against the betas for the market, size, and value factors. The graphs on the left panels use standard returns and betas. We fail to find a positive linear relationship for each of the factors, like the univariate model. The graphs on the right panels use cash-hedged returns and betas. Once we adjust all returns and factors to be in cash-hedged terms, we recover a positive, linear relationship between portfolios' expected returns and the cash-hedged market and size betas, but not for value.

One way to view the validity of an asset pricing model is to ask how well it describes the cross-section of returns; this implies a statistically significant securities market line but does not imply a positively sloped line. Economic intuition helps us to form factors so that larger betas are riskier. With factors formed on priors about what firms are riskier—growth or value, small or big, etc.—we would expect a positively sloped securities market line.

Adjusting for cash leads to a negative securities market line slope for HML. Why? Cash-adjusted growth stocks outperform cash-adjusted value stocks. There is a strong covariance between a firm's book-to-market and its cash holdings. If we formed our value factor as Low minus High, rather than High minus Low—that is, long growth stocks and short value stocks—the relationship would be positive and linear.

In Figure 7 we directly compare the standard beta and cash-hedged beta for each factor. For the size and market factors, cash-hedged betas are larger for growth portfolios and smaller for value portfolios. For the value factor, the cash-hedged beta is smaller for the 25 portfolios. The results highlight the negative covariance between value and cash holdings, and these graph results correspond to higher price of risk estimates.

5.3 Cash-Hedged Cross-sectional Asset Pricing

A formal test of the securities market line is two-pass cross-sectional asset pricing regressions. The key estimates in these regressions are the factors' prices of risk. We use a two-stage procedure to calculate the price of risk for a given factor. First, we estimate each portfolio i's beta to the risk factor using time-series regressions of each portfolio's excess return on the factor:

$$R^e_{i,t} = \alpha_i + \beta'_{i,f} f_t + \varepsilon_{i,t},\ i = 1, \ldots, N,\ t = 1, \ldots, T, \tag{9}$$

where f_t is a vector of risk factors. Then we run a cross-sectional regression of portfolio excess returns on the betas estimated in Equation 9:

$$\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f + \xi_i,\ i = 1, \dots, N. \tag{10}$$

In this test, a successful factor model will have a significant price of risk and an economically small intercept. The price of risk λ_f tells us how much an increase in expected returns is associated with a higher beta. The intercept tells us whether we can attribute all a portfolio's return to its factor loadings or if there is some unexplained component. For CAPM, $f_t = Market_t$ and the two-step procedure gives the market factor's price of risk, λ_{Market}. For multifactor pricing models like the Fama–French 4 factor model, $\mathbf{f}_t = [Market_t, HML_t, SMB_t, MOM_t]$ which estimates each factor's price of risk.

Table 4 shows the price of risk results when using the 35 test portfolios: 25 size and book-to-market sorted portfolios and 10 momentum portfolios. The first column does not confirm the CAPM in standard returns because the price of risk is statistically zero. Column 2 uses cash-hedged returns for the portfolios and market factor. In this case, price of risk is significant, and the estimate of 1.3 means that a portfolio with $\beta_{Mkt} = 1$ has a monthly expected return of 1.3%. The risk compensation in cash-hedged terms is economically large: a one standard-deviation increase in β_{Mkt} increases the annualized expected risk premium by 3pp, which is shown in the bottom row of the table.

We test a multifactor model by adding size, value, and momentum factors to $\mathbf{f}_t$. None of the four factors using standard returns are significant (column 3). Column 4 shows the results using cash-hedged returns and cash-hedged factors. Cash-hedged momentum and market have positive prices of risk, and cash-hedged value has a negative price of risk. Each price of risk point estimate is larger using cash-hedged returns. A one standard-deviation increase in β_{Mkt} increases the annualized expected risk premium by 1.2pp, and a one standard-deviation increase in each of the four factors would increase the annualized expected risk premium by nearly 9pp. The results show that combinations of the factors better explain the cross-section of returns in cash-hedged terms than standard terms.

Firm-level Characteristic Regressions We run firm-level cross-sectional regressions in Table 5, using characteristics instead of betas in the second stage, to study what types of firms hold cash and why. At the firm level, there are two possibilities: firms holding cash are less risky because they hold more cash, or firms holding more cash do so precisely because they are riskier. The cross-sectional regression using characteristics is consistent with the second story. Columns 1 and 2 show that firms with higher cash shares have higher expected equity returns. Switching from no cash on the balance sheet to 100% cash reflects a 1% increase in a firm's monthly equity return.

If cash-rich firms earn higher returns on cash, firms might hold cash depending on their ability to earn a return on cash—a form of corporate speculation. In contrast, if firms with more cash earn lower returns on cash, then firms hold cash despite the low return. Columns 3 and 4 show that firms with higher cash shares earn significantly lower returns on cash. In other words, firms hold cash despite the lower returns. Firms might choose to do so for precautionary savings and or to avoid costly external financing. The result indicates that the average firm does not hold cash because they think they can earn a high cash return.

Similarly, Table 6 shows regressions of firms' start-of-year cash share on their average cash return over the last year. Firms' cash shares are negatively correlated with past cash returns, but they hold their cash share steady when cash return volatility increases. When cash returns decrease, firms increase their cash share in response. Intuitively, cash shares should fall after low cash returns. The negative coefficient means that when cash earns a low return, firms reallocate to hold more cash.

5.4 Cash-Hedged Portfolios and Factors

Cash-hedged returns remove a common component of firms' returns, and cash-hedging makes the return covariance structure richer and more informative. We show this in two ways: first, the efficient frontier of portfolios is much steeper in cash-hedged terms, implying a tangency portfolio with more expected return per unit of risk. Second, we show that cash-hedged returns generally have higher returns and Sharpe ratios, and combinations of cash-hedged factors outperform combinations of standard factors.

Efficient Frontier A portfolio made of components with less correlated returns will have better diversification, giving more expected return per unit of risk. Since firms' cash returns are correlated, hedging cash returns helps create more diversified portfolios by estimating the efficient frontier. Figure 8 shows the efficient frontiers for the standard return and cash-hedged portfolios. In the top panel, we sort firms into 25 size and book-to-market portfolios and 10 momentum portfolios. Cash-hedging produces larger variation in the cross-section of expected returns, and the cash-hedged efficient frontier is steeper than the efficient frontier in standard return terms. The cash-hedged tangency portfolio is more efficient, reflected in the frontier's steepness. The cash-hedged tangency portfolio's Sharpe ratio is 63% higher than the standard tangency's Sharpe ratio.

Size and book-to-market are well known to covary with returns, so portfolios formed by sorting across these characteristics should have substantial differences in expected returns. Even so, cash-hedging produces greater variation in the cross-section of average returns. Thus, investors can better detect priced risk factors by using cash-hedged returns, and the benefits are larger when there is less variation in expected returns in standard terms.

What if investors are unsure of which characteristics to use as sorting variables? Cash-hedging helps protect against lousy sorting. Suppose an investor sorts portfolios based on an arbitrary characteristic, then the investor will end up with portfolios with little variation in the expected returns, and the cross-sectional regressions will struggle to find a significant price of risk for their risk factor of preference.

This logic predicts that with poorly-sorted portfolios, the tangency portfolio calculated from standard returns will have a lower Sharpe ratio than the tangency portfolio using cash-hedged returns. We sort firms into 26 portfolios based on the first letter of their ticker, which creates 26 portfolios. We effectively have nearly random samples of the market. Since we have poorly sorted stocks, each portfolio's expected return is roughly equal to the market's return with an error term. There is no clear reason a risk factor would covary with tickers starting with certain letters. But there is hope that the lousy sorting still has variation in the portfolios' cash returns.

Figure 8's bottom panel shows the efficient frontiers for the poorly-sorted portfolios in standard and cash-hedged returns. Standard portfolios have returns in a close range while cash-hedged portfolios have a much steeper efficient frontier. The annualized Sharpe ratio for the cash-hedged tangency portfolio is a 75% increase in efficiency from the standard tangency portfolio. Intuitively, cash hedging gives investors a second layer of defense when they sort their portfolios. So long as there is variation in the portfolio's cash returns, then even if the standard returns are roughly equal across the portfolios, cross-sectional regressions with cash-hedged portfolios will better pick up the price of risk.

Cash-Hedged Factors Table 7 presents the annualized returns and Sharpe ratios for the most common asset pricing factors. We show the statistics in standard terms and cash-hedged terms. The rows in the top half of the table are the simple long-short sorts without any double sorting. The bottom panel uses the same factors—which use double sorts, except for the market factor—as the cross-sectional regressions. Across most factors, the cash-hedged Sharpe ratios increase.

Intuitively, we would expect that cash-hedged returns are higher on average since we expect cash returns to be low in relative terms and have lower volatility. Whether cash-hedged premia have higher Sharpe ratios than standard premia depend on whether cash-hedged returns are high enough to offset their increased volatility. Table 7 shows that cash-hedged strategies generally have higher Sharpe ratios, so the returns are high enough to offset their higher volatility.

Cash-hedged size, momentum, and combinations of the simple long-short sorts have higher returns than their standard counterparts, but value's Sharpe ratio turns negative. For the market, size, and momentum factors, cash-hedged expected returns are larger than their standard return counterparts. The cash-hedged market factor has a Sharpe ratio of 0.63; and the cash-hedged momentum factor's Sharpe is 0.78, more than double the amount in standard terms (0.30). *HML* has lower cash-hedged returns due to the strong covariance between firms' cash shares and book-to-market.

Cash-hedging doesn't change the negative correlation between value and momentum documented in Asness et al. (2013). For both the simple long-short sorts and the factors, Table 7 shows that combinations of value, momentum, and size always have higher Sharpe ratios in cash-hedged terms than in standard terms.

Figure 9 shows the cumulative returns of the factors in standard and cash-hedged terms. Value in cash-hedged terms has performed much worse, especially during the dot-com bubble and during the Covid-19 pandemic. Cash-hedged momentum, however, has performed much better than its standard terms alternative, consistent with the robust negative relationship between value and momentum found in Asness et al. (2013).

Factor Legs Cash holdings bias the factor returns constructed from sorts on characteristics like size, book-to-market, and momentum because the long and short legs regularly have different cash holdings. Let f_t be the simple factor return, r_t^L be the return to the long leg of the factor, and r_t^S be the short leg of the factor. Then:

$$f_t = r_t^L - r_t^S \tag{11}$$

Substituting the portfolio decompositions for the long and short legs into the equation for the factor portfolio return is

$$f_t = (e_t^L - e_t^S) - (\gamma_t^L - \gamma_t^S) \tag{12}$$

The first term, $e_t^L - e_t^S$, is the return of the cash-hedged components, and the last term, $\gamma_t^L - \gamma_t^S$, is the bias in the factor's realizations due to firm cash holdings.

Figure 10 shows the net cash position for the simple factor portfolios and the net cash position after adjusting for their estimated cash holdings. When the net cash position of a factor is positive, it means that the long leg of the factor has a larger cash holding that then short leg, so that a long-short strategy ends up long the cash position. Alternatively, if the implicit cash holdings in the long and short legs of the factor were equal, then the net cash position would be zero.

The simple value portfolio has a large negative net cash position because growth stocks have larger cash holdings than value stocks. Cash returns tend to be lower than cash-hedged returns, so the outsized cash position in the short leg of the value portfolio has lower return in standard terms than in cash-hedged terms, and the overall portfolio has higher returns in standard terms. The momentum portfolio has a volatile cash position which is positive on average. The size portfolio's net cash holding is the smallest, implying the cash holdings vary less with firm size than the other characteristics. Both results correspond to the factor premia in Table 7.

All three factors have net cash shares near zero after adjusting for estimated cash holdings. The net cash position after adjusting for estimated cash holdings is not perfectly zero because our methodology lags cash-related balance sheet data to reflects investors' information set—they do not know the current quarter's data. We prefer our simple method using lagged data because it is effective, even though more involved techniques may help investors better forecast current-quarter cash balances.

5.5 Cash in Bad States

We study cash dynamics in the Covid-19 pandemic to understand the risks an investor faces when using cash-hedged strategies. Several papers document a *dash for cash* during the initial panicked stages of the Covid-19 pandemic (Acharya and Steffen, 2020; He et al., 2022). When the global pandemic began in early 2020, firms rushed to add cash to their coffers. Our average cash value methodology lets us empirically estimate the dash for cash: the average value of a dollar inside a firm grew from $1.076 in January 2020 to a $1.116 peak in November 2020. The annualized return on cash between January and April was roughly 6.1%–one of the largest annualized increases in our sample.

Figure 11 shows the value-weighted value of $1 and cash shares for our sample of the aggregate market. Both cash values and cash shares grew in 2020. Since the pandemic began, the aggregate share of cash has been over 20%, peaking at 23%, the highest cash share in our sample. Before the pandemic, cash shares were consistently under 20%. In the online appendix Figure A.1, we show that such a boost in cash values is not uncommon during bad times: cash values increased during the 1987 market crash, the 2008 financial crisis, and the Covid pandemic. The 2008 financial crisis and covid both had persistent cash value increases lasting at least 10 months, whereas cash values after the 1987 crash jumped only temporarily. Cash values also did not increase during the dot-com bubble, unsurprising given that many technology companies' cash shares were comparatively high.

6 Conclusion

Shareholders should internalize their implicit cash holdings. We study the effect of firm cash on betas and common asset pricing factors. We decompose a firm's standard stock return into the firm's cash-hedged return, cash share, and return on cash. Standard stock returns are not cash-hedged returns: standard stock returns are lower and less volatile. Common asset pricing factors have time-varying and non-zero net cash positions, and hedging implicit cash positions changes factor premia.

Some investors may prefer to have the firm manage their implicit cash positions. Indeed, some companies appear skillful at managing cash portfolios. But firms' cash management is not consistent across all firms, and many investors may want to manage their cash positions themselves.

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7 Figures

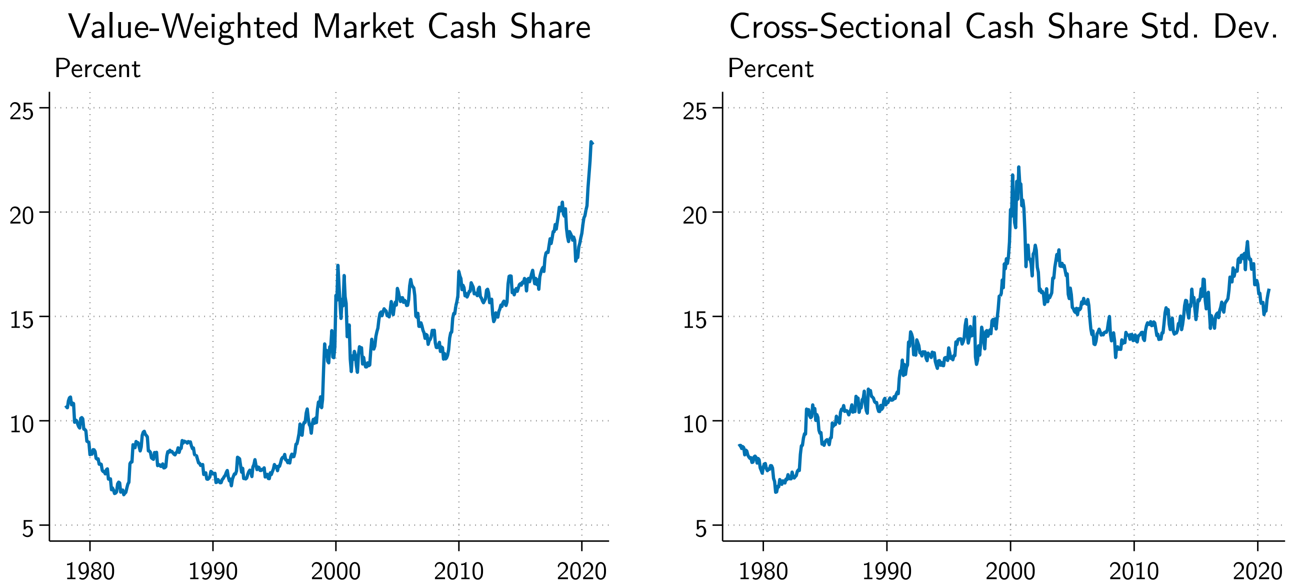

Figure 1: Cash share and cross-sectional cash share standard deviation. The left panel reports the time-series of the aggregate market's value-weighted cash share from 1978 to 2020. The cash share is the share of cash and short-term equivalents as a percent of total assets, weighted by lagged market capitalization. The right panel reports the cross-sectional standard deviation in cash-share across firms in each month.

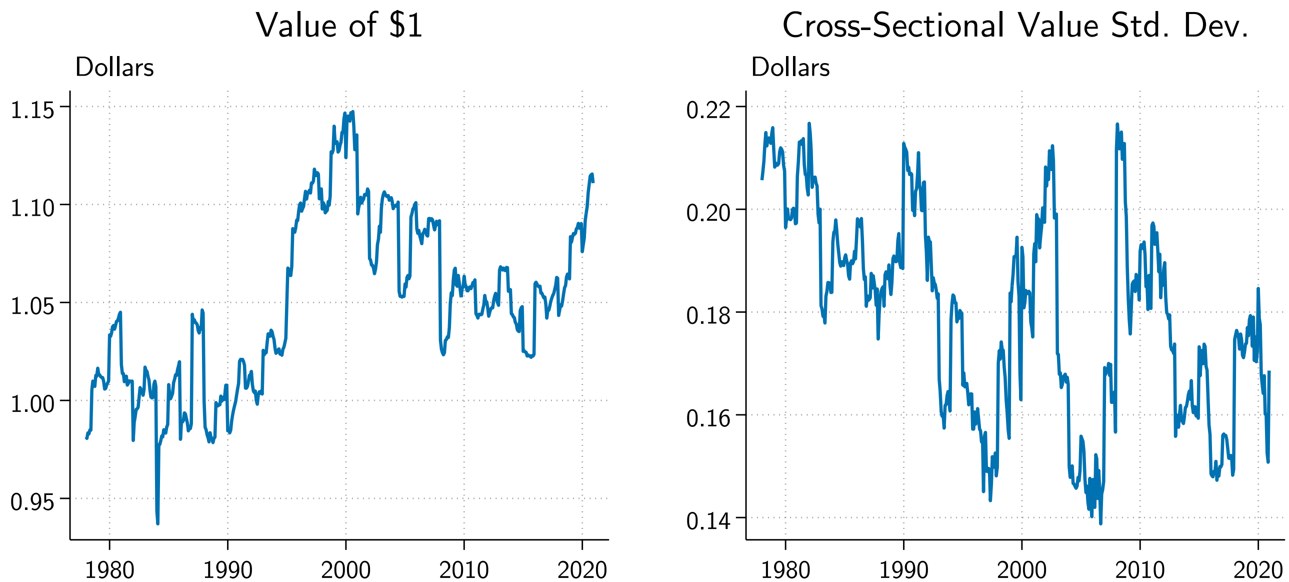

Figure 2: Value of $1 and cross-sectional value standard deviation. The left panel reports the time-series of the aggregate market's value-weighted value of $1 from 1978 to 2020. The right panel reports the cross-sectional standard deviation across firms of the value of $1.

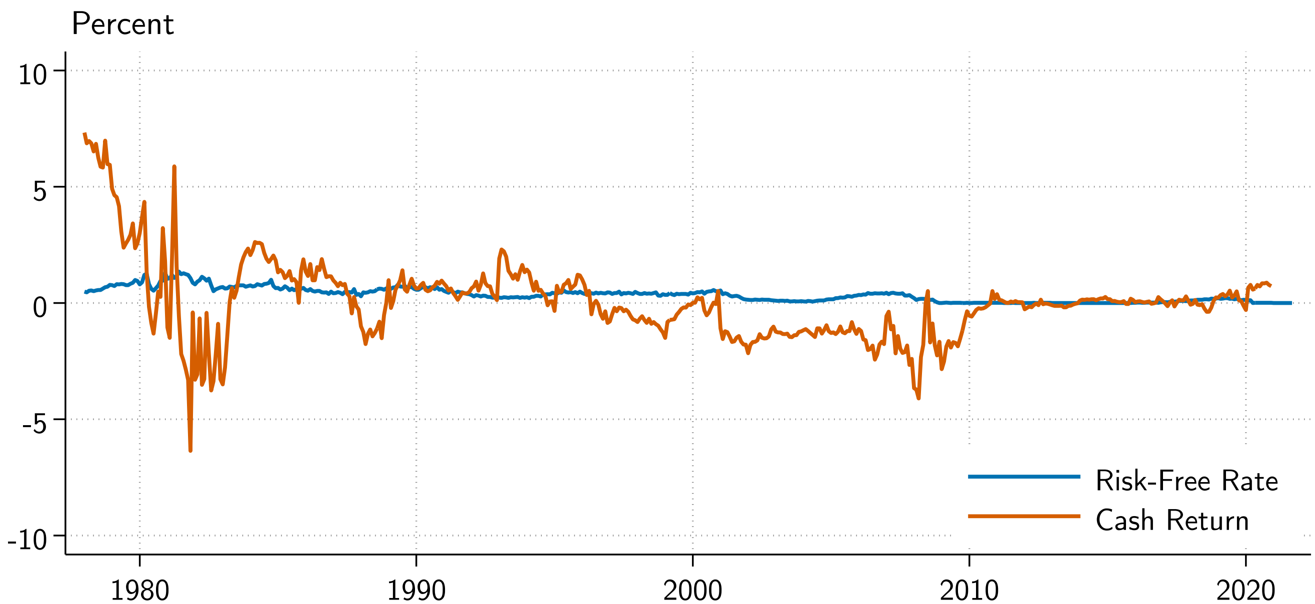

Figure 3: Monthly Cash Returns. The figure reports the value-weighted cash return and the risk-free rate.

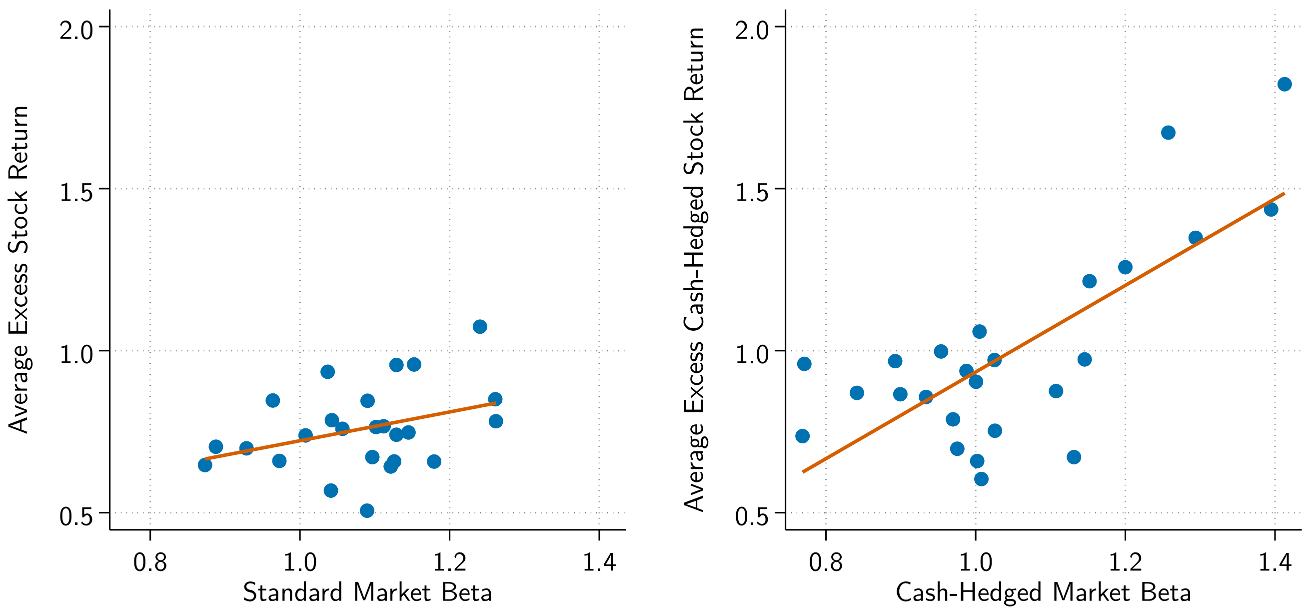

Figure 4: Securities Market Line for Market and Equity Betas. The left panel is the securities market line using the market factor and 25 size/book-to-market sorted portfolios constructed from standard returns. The right panel is the securities market line using cash-hedged returns.

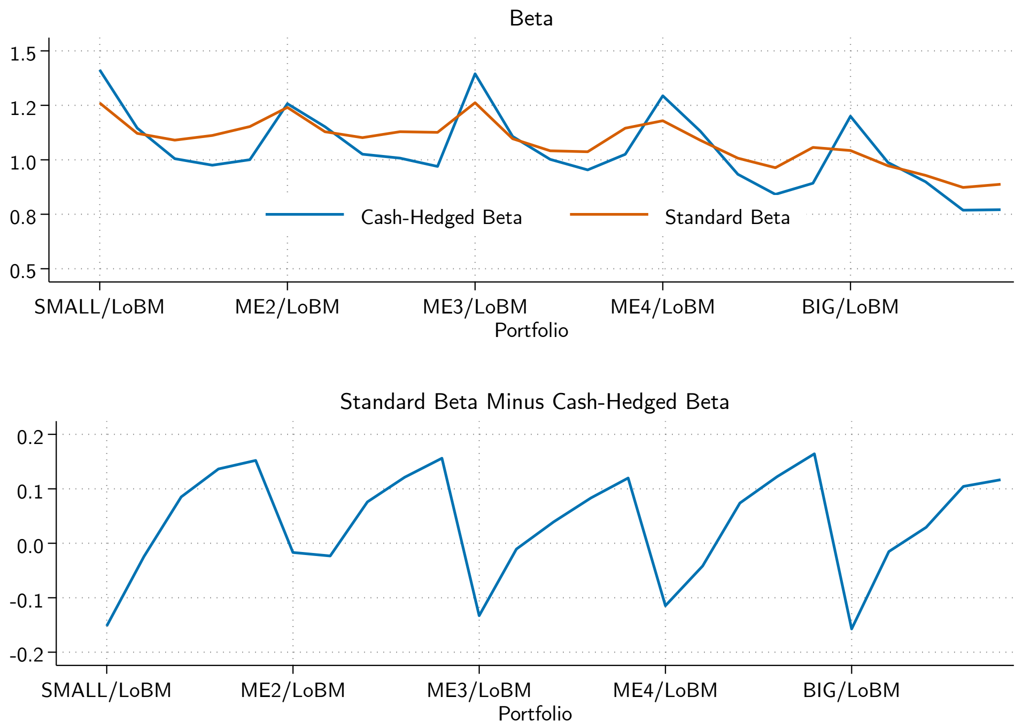

Figure 5: CAPM Beta Comparison. The top panel plots the standard beta and cash-hedged beta across the 25 size/book-to-market sorted portfolios. The portfolios are formed separately for standard and cash-hedged returns.

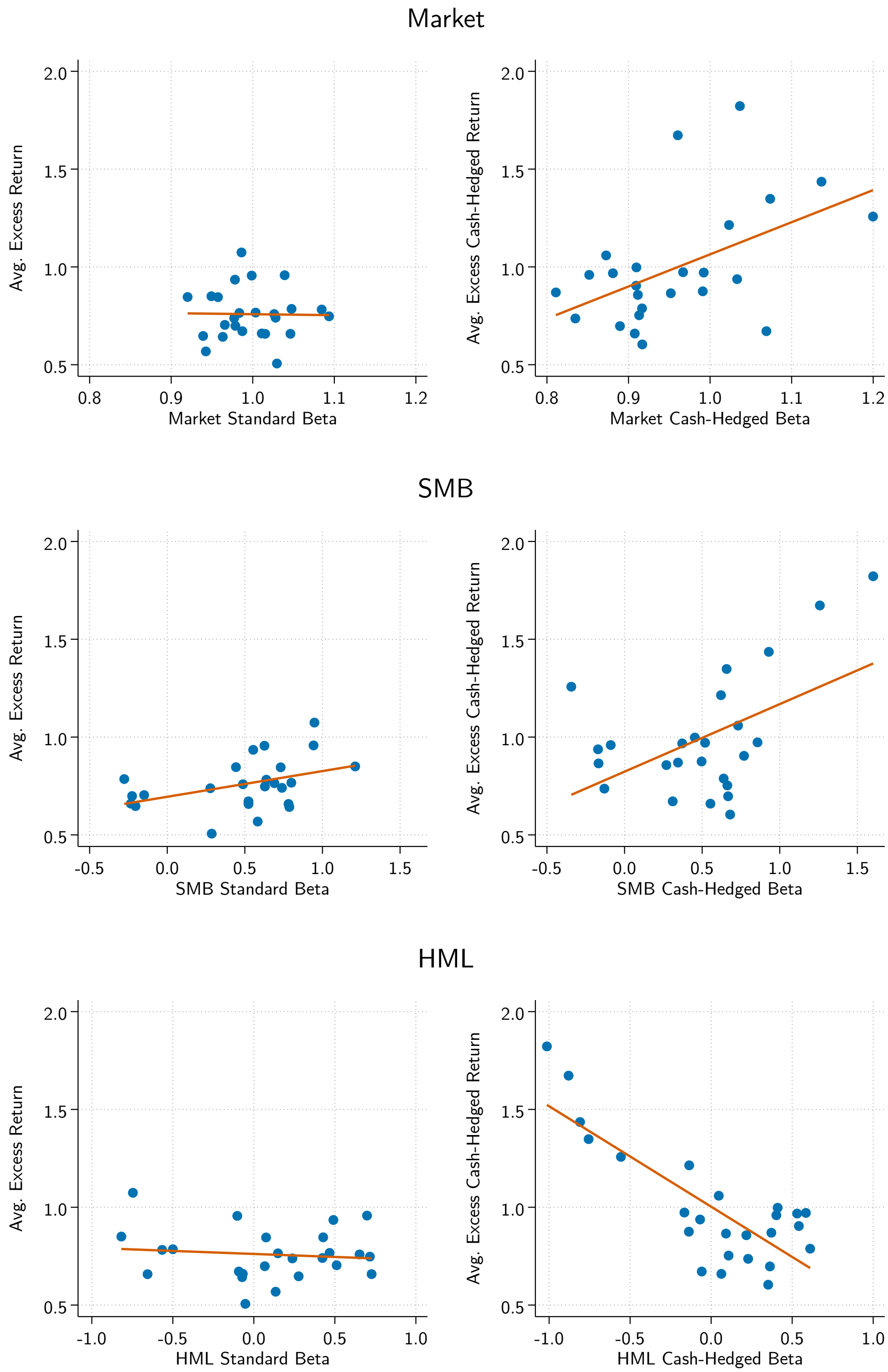

Figure 6: Returns and Betas from the Fama–French Three-Factor Model. The left panels plot the standard excess returns against the betas for each portfolio. The right panels plot portfolios' cash-hedged excess returns and cash-hedged betas. The betas in the top two graphs correspond to market betas; the betas in the middle two graphs are betas to size factors; and the betas in the bottom two graphs are betas to value factors.

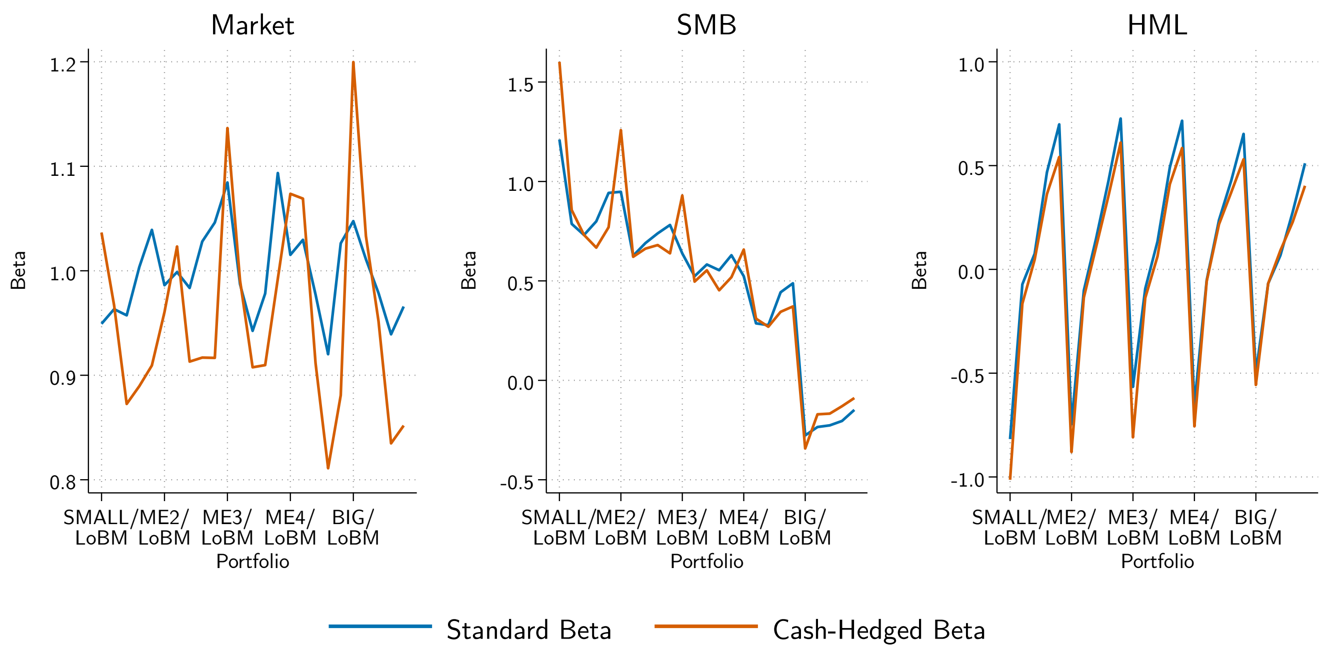

Figure 7: Standard and Cash-Hedged Betas from the Fama–French Three-Factor Model. Figure plots standard and cash-hedged betas from Fama–French three-factor model. Cash-hedged betas use cash-hedged factors and portfolio returns. The left panel plots market betas, the middle panel plots size betas, and the right panel plots value betas.

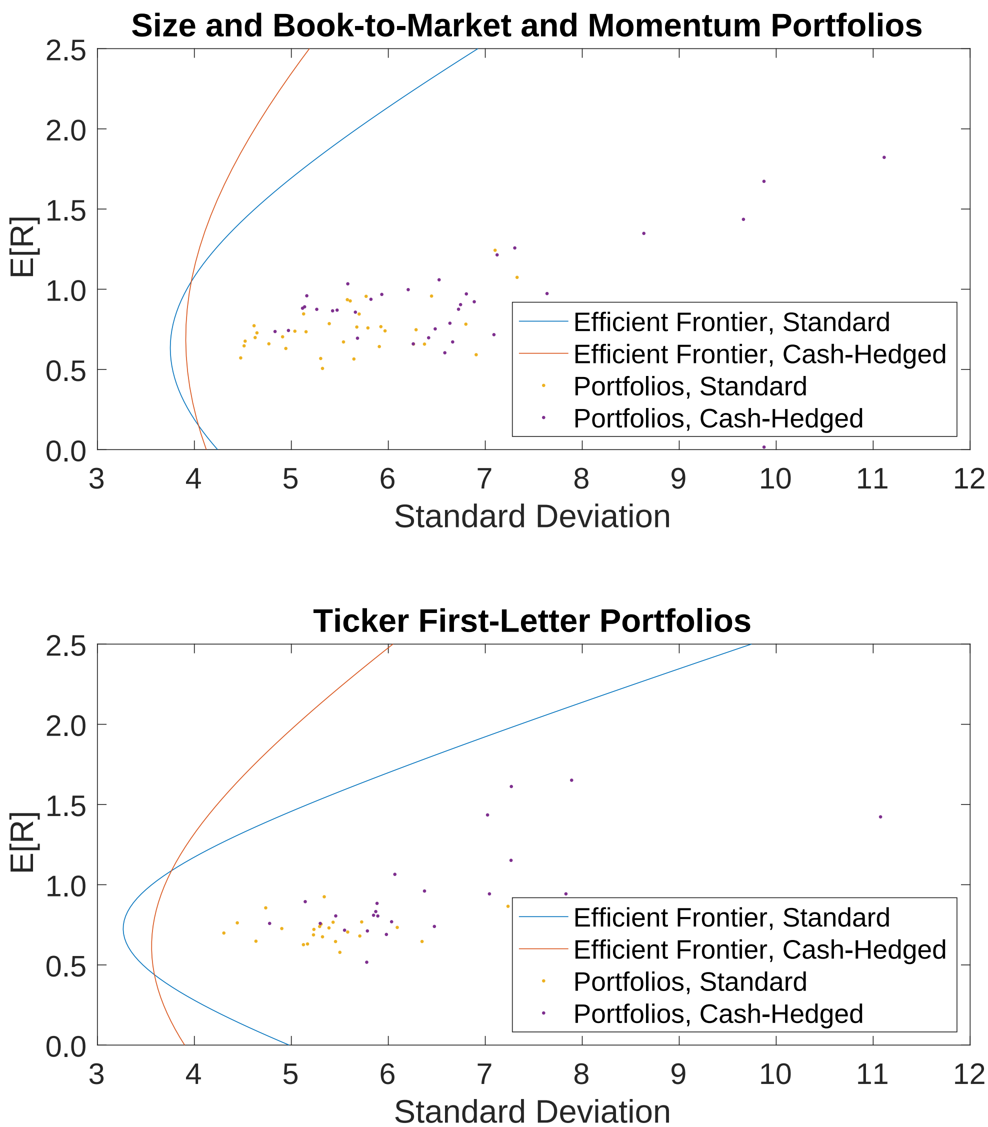

Figure 8: Efficient Frontiers for Standard and Cash-Hedged Portfolios. Figure shows the efficient frontiers for standard return portfolios and cash-hedged return portfolios. Portfolios in the top panel are 25 size and book-to-market sorted portfolios and 10 momentum sorted portfolios; portfolios in the bottom panel are sorted on the first letter of the ticker.

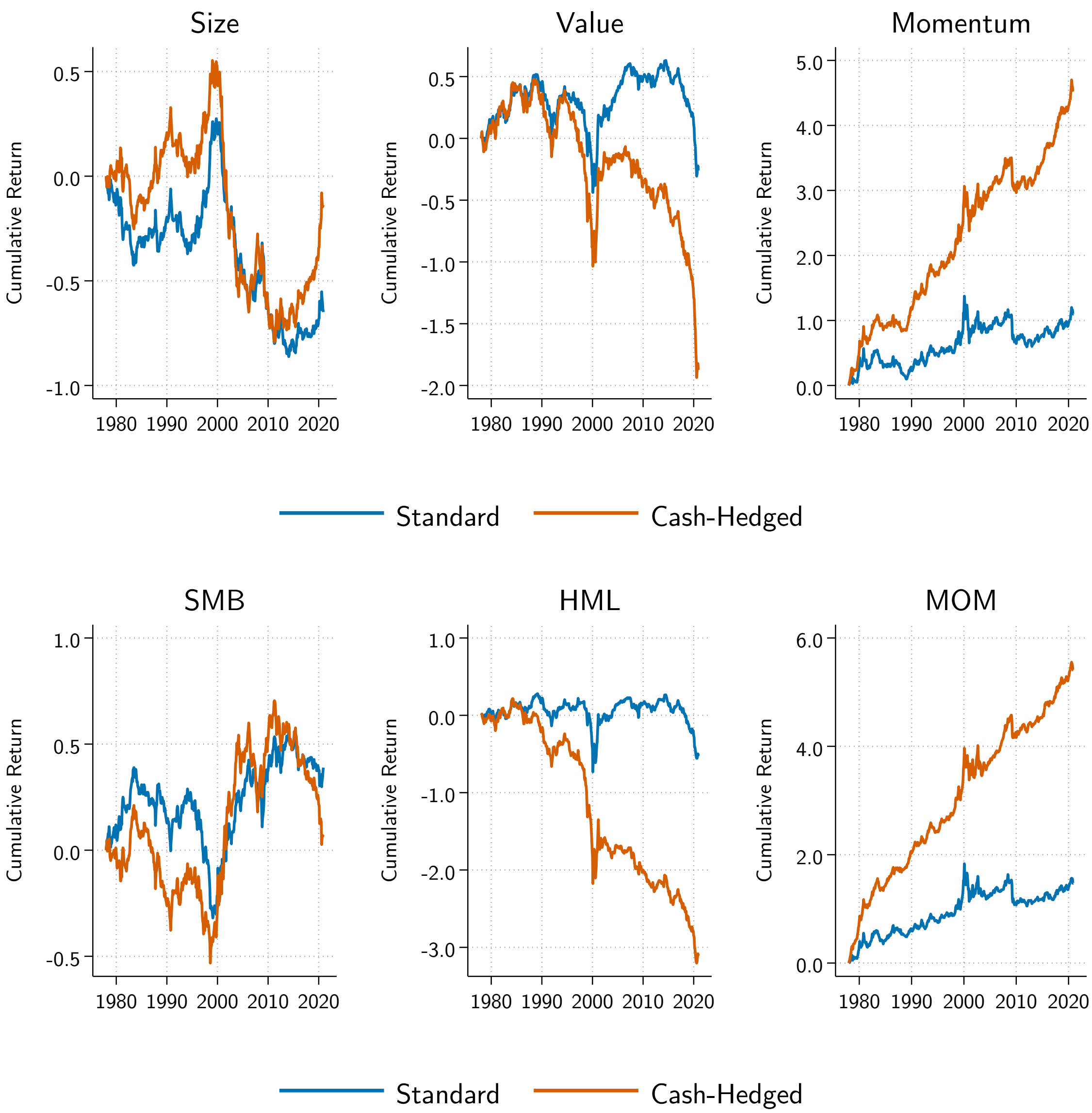

Figure 9: Cumulative Returns of Standard and Cash-Hedged Factors. Figure plots the cumulative return (sum of log returns) for size, value, and momentum factors in standard and cash-hedged returns.

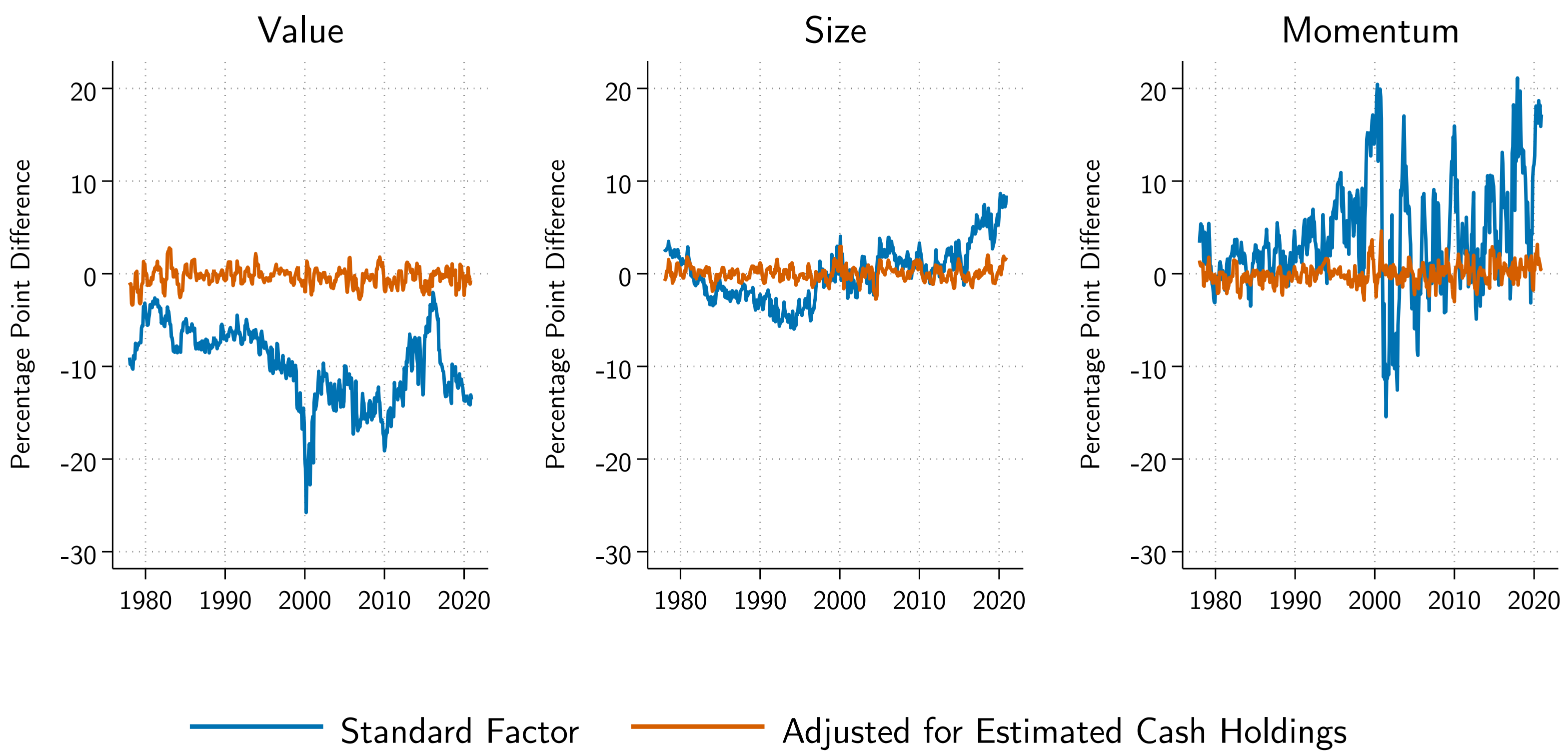

Figure 10: Factors' Net Cash Position. Figure plots the net cash position of the simple standard factors and the net cash position after adjusting for estimated net cash positions.

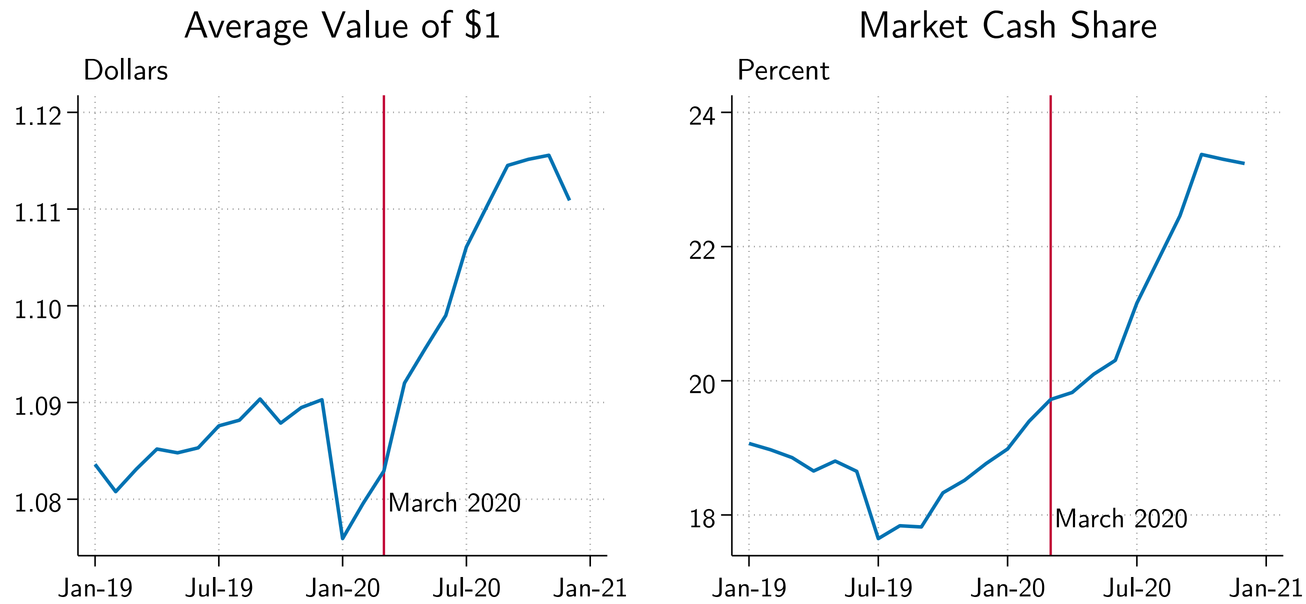

Figure 11: Cash Dynamics in Covid-19 Pandemic. Figure shows cash dynamics in the Covid-19 pandemic. The top panel reports the value-weighted average value of $1, and the bottom panel shows the value-weighted market cash share.

8 Tables

Cash Share (Percent)					
	Low	2	3	4	High
Small	24	15	11	9	7
2	22	14	10	8	7
3	21	14	10	8	6
4	18	13	10	7	5
Big	18	14	11	8	7
Average	21	14	11	8	6

Standard Returns													
Return							Standard Deviation						
	Low	2	3	4	High	High−Low		Low	2	3	4	High	Low/High
Small	0.85	0.64	0.85	0.77	0.96	0.11	Small	7.8	5.9	5.7	5.9	6.5	1.20
2	1.07	0.96	0.76	0.74	0.66	−0.42	2	7.3	5.8	5.7	6.0	6.3	1.17
3	0.78	0.67	0.57	0.93	0.75	−0.03	3	6.8	5.5	5.3	5.6	6.3	1.08
4	0.66	0.51	0.74	0.85	0.76	0.10	4	6.4	5.3	5.0	5.1	5.8	1.10
Big	0.79	0.66	0.70	0.65	0.70	−0.08	Big	5.4	4.8	4.6	4.5	4.9	1.10

Cash-Hedged Returns													
Return							Standard Deviation						
	Low	2	3	4	High	High−Low		Low	2	3	4	High	Low/High
Small	1.82	0.97	1.06	0.70	0.90	−0.92	Small	11.1	7.6	6.5	6.4	6.8	1.65
2	1.67	1.21	0.75	0.60	0.79	−0.88	2	9.9	7.1	6.5	6.6	6.6	1.49
3	1.44	0.88	0.66	1.00	0.97	−0.46	3	9.7	6.7	6.3	6.2	6.8	1.42
4	1.35	0.67	0.86	0.87	0.97	−0.38	4	8.6	6.7	5.7	5.5	5.9	1.46
Big	1.26	0.94	0.87	0.74	0.96	−0.30	Big	7.3	5.8	5.4	4.8	5.2	1.42

Table 1: Portfolio Cash Share and Returns. Table reports cash shares, average monthly returns, and return volatility for 25 size-and-book-to-market sorted portfolios in standard and cash-hedged terms.

	Equal-Weighted			Value-Weighted		
	b_t^i	e_t^i	r_t^i	b_t^i	e_t^i	r_t^i
Avg. Correlation	5.68***	15.04***	16.25***	6.84***	17.89***	18.76***
	(27.82)	(74.13)	(121.81)	(11.29)	(29.77)	(45.89)
N	100,000	100,000	100,000	100,000	100,000	100,000

Table 2: Firm-Specific Cash Returns Are Correlated. We randomly select two firms in our sample and calculate the correlation of their annual returns—either their cash returns b_t^i, standard stock returns r_t^i, or cash-hedged returns e_t^i—and repeat the process 100,000 times. We then regress the resulting 100,000 correlation coefficients on a constant. t-statistics are reported in parentheses using robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Size	BE/ME	$\beta^{p,standard}$ =	$\beta^{p,cash-hedged}$ ×	$\frac{\text{Var}(e_t^{m,xs})}{\text{Var}(r_t^{m,xs})}$ +	$\frac{-\text{Cov}(\gamma_t^p, e_t^{m,xs})}{\text{Var}(r_t^{m,xs})}$ +	$\frac{-\text{Cov}(e_t^{p,xs}, \gamma_t^m)}{\text{Var}(r_t^{m,xs})}$ +	$\frac{\text{Cov}(\gamma_t^p, \gamma_t^m)}{\text{Var}(r_t^{m,xs})}$
Small	Lo	1.26	1.41	1.39	−0.46	−0.33	0.10
	2	1.12	1.15	1.39	−0.27	−0.25	0.06
	3	1.09	1.01	1.39	−0.13	−0.21	0.03
	4	1.11	0.98	1.39	−0.06	−0.19	0.01
	Hi	1.15	1.00	1.39	−0.04	−0.20	0.01
ME2	Lo	1.24	1.26	1.39	−0.27	−0.29	0.06
	2	1.13	1.15	1.39	−0.28	−0.25	0.05
	3	1.10	1.03	1.39	−0.14	−0.22	0.03
	4	1.13	1.01	1.39	−0.08	−0.21	0.02
	Hi	1.13	0.97	1.39	−0.04	−0.19	0.01
ME3	Lo	1.26	1.39	1.39	−0.45	−0.32	0.10
	2	1.10	1.11	1.39	−0.26	−0.23	0.05
	3	1.04	1.00	1.39	−0.18	−0.21	0.04
	4	1.04	0.95	1.39	−0.12	−0.19	0.03
	Hi	1.15	1.03	1.39	−0.09	−0.21	0.02
ME4	Lo	1.18	1.29	1.39	−0.40	−0.30	0.09
	2	1.09	1.13	1.39	−0.29	−0.25	0.06
	3	1.01	0.93	1.39	−0.12	−0.19	0.02
	4	0.96	0.84	1.39	−0.06	−0.16	0.01
	Hi	1.06	0.89	1.39	−0.02	−0.17	0.01
BIG	Lo	1.04	1.20	1.39	−0.42	−0.30	0.09
	2	0.97	0.99	1.39	−0.23	−0.21	0.05
	3	0.93	0.90	1.39	−0.17	−0.18	0.04
	4	0.87	0.77	1.39	−0.06	−0.14	0.01
	Hi	0.89	0.77	1.39	−0.05	−0.14	0.01
Average		1.08	1.05	1.39	−0.19	−0.22	0.04

Table 3: Decomposition of Standard CAPM Betas. Table shows the decomposition of standard betas for 25 size and book-to-market sorted portfolios. The standard beta for each portfolio is decomposed into the cash-hedged beta, ratio of variances, and drag terms as defined in Equation 8.

	Prices of Risk: $\mathrm{E}[R_i^e] = \alpha + \beta'\lambda$			
Model	CAPM		4-Factor	
	Standard	Hedged	Standard	Hedged
Intercept	0.127	−0.342	0.240	0.039
t-FM	(0.281)	(−0.882)	(0.558)	(0.113)
t-GMM	(0.275)	(−0.822)	(0.569)	(0.102)
$\mathrm{Mkt}-\mathrm{R_f}$	0.590	1.285	0.472	0.947
t-FM	(1.203)	(2.87)	(0.992)	(2.288)
t-GMM	(1.187)	(2.718)	(1.003)	(2.146)
SMB			0.131	0.174
t-FM			(1.089)	(1.178)
t-GMM			(1.086)	(1.146)
HML			−0.034	−0.563
t-FM			(−0.21)	(−2.675)
t-GMM			(−0.207)	(−2.574)
MOM			0.307	1.232
t-FM			(1.494)	(4.894)
t-GMM			(1.486)	(4.913)
Diagnostics				
MAPE (%)	0.11	0.24	0.09	0.23
Mean Time-Series R^2	0.72	0.67	0.86	0.81
Months (T)	516	516	516	516
Portfolios (N)	35	35	35	35
GRS p-value	0.06	0.00	0.06	0.00
Mkt Risk Premium ($\sigma^\beta \times \lambda^{Mkt}$)	0.78	3.06	0.29	1.23
Factors' Risk Premium ($\sigma^\beta \cdot \lambda$)	0.78	3.06	2.00	8.56

Table 4: Cross-Sectional Price of Risk. Table presents the pricing results 25 size-value and 10 momentum portfolios. Coefficient presents the price of risk, λ. *Standard* columns gives the results when testing standard (i.e., not cash-hedged) portfolio returns on standard factors. *Hedged* column gives the results when testing cash-hedged portfolios on cash-hedged factors. All returns are excess returns. MAPE is mean absolute pricing error. GRS is the Gibbons-Ross-Shaken test whether the pricing errors are jointly zero. *Mkt Risk Premium* is the annualized increased in risk premium associated with a one standard deviation increase in beta; *Factors' risk premium* is the same except the sum of the absolute value of the annualized increase in risk premium for each factor in the model, excluding the intercept.

	Standard Return		Cash Return	
	(1)	(2)	(3)	(4)
Intercept	1.029	1.390	1.686	9.215
	(4.77)	(1.87)	(11.33)	(4.75)
Cash Share	0.973	1.196	−9.572	−5.872
	(2.06)	(2.88)	(−4.31)	(−2.48)
$\ln(Size)$		−0.024		−0.424
		(−0.6)		(−3.14)
$\ln(B/M)$		0.045		1.910
		(0.65)		(7.75)
Months (T)	515	515	515	515
Firms (N)	2,062	2,062	2,062	2062

Table 5: Firm-Level Cross-Sectional Regression. Table presents cross-sectional regressions at the firm-level using characteristics of cash share, size, and book-to-market.

	(1) Cash Share	(2) Cash Share	(3) Cash Share	(4) Cash Share	(5) Cash Share	(6) Cash Share
Lagged Cash Return	-0.008^{***}	-0.006^{**}			-0.008^{***}	-0.006^{***}
	(-3.24)	(-2.55)			(-3.23)	(-2.76)
Lagged Cash Return Volatility			0.001	0.012^{***}	0.000	0.012^{***}
			(0.23)	(3.48)	(0.01)	(3.32)
N	15,981	15,981	15,981	15,981	15,981	15,981
Adj. R^2	0.00	0.23	0.00	0.23	0.00	0.23
Year FE	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes

Table 6: Cash Shares and Past Cash Returns. Table presents regressions of firms' start-of-year cash share on average cash return and cash return volatility over the previous year. t-statistics are reported in parentheses using robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Factors	Standard Returns		Cash-Hedged Returns		Difference	
	Average	Sharpe	Average	Sharpe	E[R]	Sharpe
Long-Short Sorts						
Value	0.07	0.01	−3.16	−0.22	−3.23	−0.22
Size	−1.08	−0.11	0.28	0.02	1.36	0.14
Mom	3.87	0.24	13.11	0.65	9.24	0.42
$\frac{1}{2}Value + \frac{1}{2}Mom$	1.96	0.28	4.69	0.51	2.73	0.23
$\frac{1}{3}Value + \frac{1}{3}Mom + \frac{1}{3}Size$	0.94	0.17	3.20	0.44	2.26	0.27
Factors						
Market	8.88	0.55	12.17	0.63	3.29	0.08
HML	−0.42	−0.03	−5.68	−0.36	−5.27	−0.33
SMB	1.36	0.15	0.81	0.07	−0.55	−0.07
MOM	4.68	0.30	15.26	0.78	10.58	0.48
$\frac{1}{2}HML + \frac{1}{2}MOM$	2.10	0.34	4.31	0.46	2.20	0.13
$\frac{1}{3}HML + \frac{1}{3}MOM + \frac{1}{3}SMB$	1.85	0.37	3.13	0.50	1.27	0.13

Table 7: Factor Premia. Table presents annualized returns and Sharpe ratios for factors described in Section 3.

A Online Appendix

A.1 Data and Variable Construction

Sample Our stock sample's construction begins with all U.S. stocks (sharecodes 10 and 11) traded on the NYSE, AMEX, and NASDQ, with share prices greater than one dollar at the end of the prior month. We exclude REITS, ADRs, preferred shares, and we require stocks to have monthly returns for the previous 12 months to construct the momentum characteristic. We exclude financial firms (SIC codes 6000–6799). Following Fama and French (1992), we match book equity data for fiscal year-end in calendar date $t-1$ with returns for July t to June $t+1$. We require stocks to have book equity for fiscal year-end in calendar date $t-1$, and we require stocks to have share prices and shares outstanding for the previous month. These conditions are necessary for constructing the book-to-market and size characteristics. We require firms' book-to-market ratios and market capitalization are greater than zero.

We chose a six-month lag for the cash share to be consistent with the construction of the book-to-market variable. A six-month lag also makes the variables' information relatively recent without risking the use of financial information before it's available to investors. Impink et al. (2012) report 91% of 10Ks between 1999 and 2006 are filed within 90 days of the fiscal year-end. Alford et al. (1994) report 20% of firms between 1977 and 1985 filed 10Ks more than 90 days after fiscal year-end. Only 2% of firms file 10Ks more than 150 days after fiscal year-end. The paper's six-month lag for BEME and cash shares could contain information for this 2% of firms before it's available to the public. But the average market cap of a firm filing more than 150 days after fiscal year-end is $4.9 million. The smallest firm's market capitalization in our sample between 1977 and 1985 is $54 million. The 2% of firms where financial statements may not be available within six months of fiscal year-end are likely too small to be in our sample.

Our sample runs from January 1978 to December 2020, but we use observations from 1976 to the end of 1977 to construct some of the paper's variables. We do not use the years 1976 and 1977 to construct factor and test portfolios because many of the require variables are unavailable before 1976.

Compustat notes that cash and short-term investments "includes, but is not limited to (1) Cash in escrow, unless legally restricted, in which case it is included in Current Assets – Other, (2) Good faith and clearing house deposits for brokerage firms, (3) Government and other marketable securities, including stocks and bonds, listed as short-term, (4) Letters of credit, (5) Margin deposits on commodity futures contracts, (6) Time, demand and certificates of deposit, (7) the total of a bank's currency and coin, plus its reserves with the Federal Reserve Bank and balances with other banks, (8) Restricted cash." The item also excludes "(1) Money due from sale of debentures, included in Receivables – Other Current, (2) Commercial paper issued by unconsolidated subsidiaries to the parent company, included in Receivables – Other Current, (3) Bullion, bullion in transit, uranium in transit, etc., included in Inventories – Raw Materials."

We use Asness et al. (2013)'s sample selection to create a liquid sample of stocks with low trading costs for moderately-sized trade volumes. Each month we rank stocks by their market capitalization at the beginning of the month, beginning with the largest stock by market capitalization and ending with the smallest stock by market capitalization. Beginning with the largest stock, we incrementally add stocks to the current month's stock sample until the stock sample makes up 90% of the stock market's total market capitalization. Asness et al. (2013) report the stocks included in the sample, on average, make up the largest 17% of firms in the United States.

To estimate firms' cash returns, we also use conditions from Faulkender and Wang (2006) to build our stock sample. We exclude utility firms from our sample (SIC codes 4900–4999). We require firms have non-missing observations for the following Compustat variables during the current and previous fiscal year: cash and short-term securities, total assets, income before extraordinary items, common stock dividends, and the total debt, including current debt or total long-term debt. We also use the following Compustat variables for the present and previous fiscal years but replace missing observations with zero: sales of common and preferred stock, purchases of common and preferred stock, long-term debt issuance, long-term debt reduction, research and development expense, and interest expense. Setting these variables to zero may introduce measurement error into our cash return estimates. But these variables are required for estimating cash returns using Faulkender and Wang (2006). Dropping observations where these variables' values are missing would create a prohibitively small sample.

A.2 Breakpoints

To estimate the marginal value of cash, we use NYSE breakpoints from Ken French's website for the size and BEME quintiles. We use firm ME at the beginning of month t and the ME breakpoint for month t to determine a stock's ME quintile. We use the current year's BEME breakpoint to assign stocks BEME quintiles for July to December. We use the previous year's BEME breakpoint to assign stocks BEME quintiles for January through June of the current year. We align stocks' BEME values with BEME breakpoints because the BEME breakpoints are updated at the beginning of each July. July through December of year t and January through June of year $t+1$ form one, complete BEME *breakpoint year*. Months are assigned to BEME breakpoint years in the same manner months are assigned to fiscal years.

A.3 Multivariate Beta Decomposition

We show the beta decomposition for a multi-factor model. We focus on the Fama–French three-factor model. We use the Frisch-Waugh-Lovell Theorem (FWL) to write each factor's standard beta as a function of the factor's cash-hedged beta and the adjustment term. We describe the process for *HML*, and the procedure is similar for *SMB* and the market. For the three-factor Fama–French asset pricing model, the time-series regression for each portfolio p is:

$$r_t^{p,xs} = \alpha + r_t^{m,xs}\beta^{p,standard} + r_t^{SMB}\beta^{p,SMB} + r_t^{HML}\beta^{p,HML} + e_t$$

We use the FWL procedure to decompose the *HML* standard beta $\beta^{p,HML}$. The procedure is similar for $\beta^{p,SMB}$ and $\beta^{p,standard}$.

1. Regress $r_t^{p,xs}$ onto $r_t^{m,xs}$ and r_t^{SMB}. Define the residuals as $\tilde{r}_t^{p,xs}$.

2. Regress r_t^{HML} onto $r_t^{m,xs}$ and r_t^{SMB}. Define the residuals as $\tilde{r}_t^{HML}$.

3. Regress $\tilde{r}_t^{p,xs}$ on $\tilde{r}_t^{HML}$. The coefficient on $\tilde{r}_t^{HML}$ is equivalent to $\beta^{p,HML}$ from the time-series regression.

Let us construct x_z as a matrix using three vectors $x_z = [1, r^{m,xs}, r^{SMB}]$, where 1 is a $T \times 1$ vector of ones, and $r^{m,xs}$ and r^{SMB} are vectors of the excess standard return and SMB return. Let $\beta_z = [\alpha; \beta^{p,standard}; \beta^{SMB}]$ be the 3×1 vector of coefficients from the first regression. Then:

$$\tilde{r}_t^{p,xs} = r_t^{p,xs} - x_z\beta_z = \underbrace{(1 - x_z(x_z'x_z)^{-1}x_z')}_{\equiv \mathcal{Q}_z} r_t^{p,xs}$$

Let us define $\mathcal{Q}_z = (1 - x_z(x_z'x_z)^{-1}x_z)$, and let $\mathcal{Q}_z$ be the operator that transforms any variable x into $\tilde{x}$ so that $r_t^{p,xs} = e_t^{p,xs} - \gamma_t^p$ and $\mathcal{Q}_z r_t^{p,xs} = \mathcal{Q}_z e_t^{p,xs} - \mathcal{Q}_z\gamma_t^p$. As before, we can decompose standard return $r_t^{p,xs}$ into a cash-hedged component and the remaining component γ_t^p We can also write $\tilde{r}_t^{p,xs}$ as:

$$\tilde{r}_t^{p,xs} = \mathcal{Q}_z r_t^{p,xs} = \mathcal{Q}_z(e_t^{p,xs} - \gamma_t^p) = \tilde{e}_t^{p,xs} - \tilde{\gamma}_t^p$$

We analogously create $\tilde{r}_t^{HML} = \tilde{e}_t^{HML} - \tilde{\gamma}_t^{HML}$, where e_t^{HML} is created from the same 6 portfolios as r_t^{HML}. Then we can decompose the *HML* beta from the three-factor regression in the following way:

$$\underbrace{\beta^{p,HML,3factor}}_{\substack{\text{HML standard}\\ \text{stock beta}}} = \frac{cov(\tilde{r}_t^{p,xs}, \tilde{r}_t^{HML})}{var(\tilde{r}_t^{HML})}$$

$$= \underbrace{\left(\frac{cov(\tilde{e}_t^{p,xs}, \tilde{e}_t^{HML})}{var(\tilde{e}_t^{HML})}\right)}_{\substack{\text{HML cash-hedged beta}\\ =\beta^{p,HML,cash-hedged,3factor}}} \underbrace{\left(\frac{var(\tilde{e}_t^{HML})}{var(\tilde{r}_t^{HML})}\right)}_{\text{ratio of variances}} \tag{13}$$

$$+ \frac{-cov(\tilde{\gamma}_t^{p}, \tilde{e}_t^{HML}) - cov(\tilde{e}_t^{p,xs}, \tilde{\gamma}_t^{HML}) + cov(\tilde{\gamma}_t^{p}, \tilde{\gamma}_t^{HML})}{var(\tilde{r}_t^{HML})}$$

Using this equation, we decompose *HML* betas into the *HML* cash-hedged beta multiplied by the ratio of the variances (of the cash-hedged component of *HML* to the standard *HML* returns), plus an adjustment term. Analogous decompositions for *SMB* beta and market beta of the three-factor Fama-French model switch out the parts in x_z and β_z.

Tables A3, A4, and A5 show the multivariate beta decompositions for the market, size, and value factors using the three-factor model. For the value factor, there is a large difference between the standard factor and the cash-hedged component. On average, the 25 portfolios have a *HML* beta of 0.10, but a cash-hedged *HML* beta of 0.01. The cash-hedged component of *HML* is about 50% more volatile than the standard factor, and the volatility and adjustment terms do not offset each other as much as for size and the market factors.

For SMB, the cash-hedged component of *SMB* is also about 50% more volatile than the overall factor. The market factor decomposition using the three-factor model is like the CAPM results.

A.4 Cash and Book-to-Market Correlations

Table 1 shows the equal-weighted cash share and standard and cash-hedged return statistics for 25 size and book-to-market portfolios. On average, growth stocks with low book-to-market have large cash shares. Portfolios with the lowest quintile book-to-market have an average cash share of 20% compared to 6% for portfolios with the highest quintile book-to-market.

In standard return terms, low book-to-market portfolios have higher returns but *less* volatile returns. This is unexpected because we expect returns to be higher to compensate for higher volatility. In cash-hedged terms, all portfolios have higher volatility, but growth stocks have a greater jump in volatility. Now returns line up with risk and volatility. Growth stocks have higher returns and more volatile returns.

A.5 Tables

	Individual stock i	Value-Weighted Portfolio p, including $p = m$
Stock Return	$r_t^i = (1 - w_t^i)e_t^i + w_t^i b_t^i$	$r_t^p = \sum_{i \in p} v_t^i r_t^i$
Non-cash Return	$e_t^i = \frac{r_t^i - w_t^i b_t^i}{(1 - w_t^i)}$	$e_t^p = \sum_{i \in p} v_t^i e_t^i$
Excess Stock Return	$r_t^{i,xs} = r_t^i - r_t^f$	$r_t^{p,xs} = \sum_{i \in p} v_t^i r_t^{i,xs} = r_t^p - r_t^f$
Excess Non-cash Return	$e_t^{i,xs} = e_t^i - r_t^f$	$e_t^{p,xs} = \sum_{i \in p} v_t^i e_t^{i,xs} = e_t^p - r_t^f$

Table A1: Summary of Return Decompositions.

	$r_{i,t} - R^B_{i,t}$
ΔC_t	1.285***
	(0.032)
ΔE_t	0.718***
	(0.015)
ΔNA_t	0.200***
	(0.007)
ΔRD_t	1.222***
	(0.143)
ΔI_t	−0.581
	(0.406)
ΔD_t	2.967***
	(0.226)
C_{t-1}	0.159***
	(0.009)
L_t	−0.296***
	(0.007)
NF_t	−0.113***
	(0.013)
$C_{t-1} \times \Delta C_t$	−0.789***
	(0.064)
$L_t \times \Delta C_t$	−1.061***
	(0.067)
Constant	0.013***
	(0.002)
Observations	81,263
Adjusted R^2	0.16

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Marginal cash value regression using Faulkender and Wang (2006) specification. The regression's explanatory variable is risk-adjusted annual, fiscal year stock returns. Risk-adjusted returns are computed as the difference between a firm's stock return and the return of the Fama and French (1992) portfolio with the most similar size and book-to-market characteristics. All of the explanatory variables except L_{it} are scaled by lagged market value of equity. The explanatory variables are: C_t is cash. E_t is income before extraordinary items plus interest, deferred tax credits, and investment tax credits. NA_t is total assets less cash holdings. I_t is interest expense. D_t is common dividends paid. L_t is market leverage. NF_t is the total equity issuance minus equity repurchases plus debt issuance minus debt redemption. RD_t is research and development expense. The subscript t indicates at the end of year t. ΔX_t is the first difference of variable X_t, i.e. $X_t - X_{t-1}$. Robust standard errors are reported in parentheses.

Size	BE/ME	$\beta^{p,Mkt,3factor}$	$=$	$\beta^{p,Mkt,cash-hedged,3factor}$	$\times$	$\frac{var(\tilde{e}_t^{Mkt})}{var(\tilde{r}_t^{Mkt})}$	$+$	$\frac{-cov(\tilde{\gamma}_t^{p},\tilde{e}_t^{Mkt})}{var(\tilde{r}_t^{Market})}$	$+$	$\frac{-cov(\tilde{e}_t^{p,xs},\tilde{\gamma}_t^{Mkt})}{var(\tilde{r}_t^{Mkt})}$	$+$	$\frac{cov(\tilde{\gamma}_t^{p},\tilde{\gamma}_t^{Mkt})}{var(\tilde{r}_t^{Mkt})}$
Small	Lo	0.95		1.04		1.37		−0.33		−0.22		0.07
	2	0.96		0.97		1.37		−0.21		−0.20		0.05
	3	0.96		0.87		1.37		−0.10		−0.17		0.03
	4	1.00		0.89		1.37		−0.06		−0.17		0.01
	Hi	1.04		0.91		1.37		−0.03		−0.19		0.01
ME2	Lo	0.99		0.96		1.37		−0.17		−0.20		0.04
	2	1.00		1.02		1.37		−0.25		−0.20		0.05
	3	0.98		0.91		1.37		−0.11		−0.18		0.03
	4	1.03		0.92		1.37		−0.06		−0.19		0.02
	Hi	1.05		0.92		1.37		−0.04		−0.18		0.01
ME3	Lo	1.08		1.14		1.37		−0.31		−0.24		0.07
	2	0.99		0.99		1.37		−0.22		−0.19		0.04
	3	0.94		0.91		1.37		−0.15		−0.19		0.04
	4	0.98		0.91		1.37		−0.11		−0.18		0.02
	Hi	1.09		0.99		1.37		−0.08		−0.20		0.02
ME4	Lo	1.02		1.07		1.37		−0.30		−0.22		0.07
	2	1.03		1.07		1.37		−0.27		−0.22		0.06
	3	0.98		0.91		1.37		−0.11		−0.19		0.02
	4	0.92		0.81		1.37		−0.06		−0.15		0.01
	Hi	1.03		0.88		1.37		−0.02		−0.17		0.01
BIG	Lo	1.05		1.20		1.37		−0.41		−0.28		0.09
	2	1.01		1.03		1.37		−0.24		−0.21		0.05
	3	0.98		0.95		1.37		−0.18		−0.19		0.04
	4	0.94		0.83		1.37		−0.06		−0.15		0.01
	Hi	0.97		0.85		1.37		−0.05		−0.17		0.01
Average		1.00		0.96		1.37		−0.16		−0.19		0.04

Table A3: Decomposition of Standard Market Beta. Table shows the decomposition of the standard market beta from the three-factor model for 25 size and book-to-market sorted portfolios. The standard beta is decomposed into the cash-hedged beta, ratio of variances, and an adjustment term.

Size	BE/ME	$\beta^{p,SMB,3factor}$	$=$	$\beta^{p,SMB,cash-hedged,3factor}$	$\times$	$\frac{var(\tilde{e}_t^{SMB})}{var(\tilde{r}_t^{SMB})}$	$+$	$\frac{-cov(\tilde{\gamma}_t^p,\tilde{e}_t^{SMB})}{var(\tilde{r}_t^{SMB})}$	$+$	$\frac{-cov(\tilde{e}_t^{p,xs},\tilde{\gamma}_t^{SMB})}{var(\tilde{r}_t^{SMB})}$	$+$	$\frac{cov(\tilde{\gamma}_t^p,\tilde{\gamma}_t^{SMB})}{var(\tilde{r}_t^{SMB})}$
Small	Lo	1.21		1.60		1.53		−1.01		−0.79		0.56
	2	0.79		0.86		1.53		−0.41		−0.30		0.18
	3	0.73		0.73		1.53		−0.26		−0.24		0.12
	4	0.80		0.67		1.53		−0.11		−0.20		0.08
	Hi	0.94		0.77		1.53		−0.10		−0.17		0.03
ME2	Lo	0.95		1.26		1.53		−0.78		−0.65		0.45
	2	0.63		0.62		1.53		−0.20		−0.21		0.09
	3	0.69		0.66		1.53		−0.20		−0.21		0.08
	4	0.74		0.68		1.53		−0.19		−0.18		0.07
	Hi	0.78		0.64		1.53		−0.07		−0.15		0.03
ME3	Lo	0.64		0.93		1.53		−0.68		−0.35		0.24
	2	0.52		0.50		1.53		−0.17		−0.12		0.06
	3	0.58		0.55		1.53		−0.17		−0.17		0.08
	4	0.55		0.45		1.53		−0.08		−0.09		0.03
	Hi	0.63		0.52		1.53		−0.10		−0.10		0.03
ME4	Lo	0.52		0.66		1.53		−0.42		−0.19		0.13
	2	0.29		0.31		1.53		−0.14		−0.08		0.03
	3	0.28		0.27		1.53		−0.07		−0.07		0.00
	4	0.44		0.34		1.53		−0.04		−0.05		0.01
	Hi	0.49		0.37		1.53		−0.03		−0.06		0.00
BIG	Lo	−0.28		−0.34		1.53		0.14		0.18		−0.08
	2	−0.23		−0.17		1.53		0.04		0.00		−0.01
	3	−0.23		−0.17		1.53		0.01		0.04		−0.02
	4	−0.20		−0.13		1.53		−0.01		0.01		0.00
	Hi	−0.15		−0.09		1.53		−0.01		0.00		−0.01
Average		0.48		0.50		1.53		−0.20		−0.17		0.09

Table A4: Decomposition of Standard SMB Beta. Table shows the decomposition of the standard *SMB* beta from the three-factor model for 25 size and book-to-market sorted portfolios. The standard beta is decomposed into the cash-hedged beta, ratio of variances, and an adjustment term.

Size	BE/ME	$\beta^{p,HML,3factor}$	$=$	$\beta^{p,HML,cash-hedged,3factor}$	$\times$	$\frac{var(\tilde{e}_t^{HML})}{var(\tilde{r}_t^{HML})}$	$+$	$\frac{-cov(\tilde{\gamma}_t^{p},\tilde{e}_t^{HML})}{var(\tilde{r}_t^{HML})}$	$+$	$\frac{-cov(\tilde{e}_t^{p,xs},\tilde{\gamma}_t^{HML})}{var(\tilde{r}_t^{HML})}$	$+$	$\frac{cov(\tilde{\gamma}_t^{p},\tilde{\gamma}_t^{HML})}{var(\tilde{r}_t^{HML})}$
Small	Lo	−0.82		−1.01		1.53		0.56		0.49		−0.31
	2	−0.07		−0.17		1.53		0.19		0.09		−0.10
	3	0.08		0.05		1.53		0.03		0.01		−0.04
	4	0.47		0.36		1.53		0.01		−0.10		0.00
	Hi	0.70		0.54		1.53		−0.02		−0.12		0.01
ME2	Lo	−0.75		−0.88		1.53		0.43		0.44		−0.27
	2	−0.10		−0.14		1.53		0.08		0.08		−0.06
	3	0.15		0.11		1.53		0.02		−0.01		−0.02
	4	0.42		0.35		1.53		−0.04		−0.07		0.00
	Hi	0.73		0.61		1.53		−0.08		−0.15		0.02
ME3	Lo	−0.57		−0.81		1.53		0.55		0.37		−0.25
	2	−0.09		−0.14		1.53		0.12		0.06		−0.06
	3	0.13		0.06		1.53		0.06		0.03		−0.05
	4	0.49		0.41		1.53		−0.02		−0.12		0.00
	Hi	0.72		0.58		1.53		−0.05		−0.14		0.01
ME4	Lo	−0.66		−0.76		1.53		0.39		0.24		−0.14
	2	−0.05		−0.06		1.53		0.03		0.05		−0.04
	3	0.24		0.22		1.53		−0.06		−0.04		0.01
	4	0.43		0.37		1.53		−0.03		−0.12		0.01
	Hi	0.65		0.53		1.53		−0.03		−0.13		0.00
BIG	Lo	−0.50		−0.56		1.53		0.26		0.17		−0.08
	2	−0.07		−0.07		1.53		0.01		0.05		−0.02
	3	0.07		0.09		1.53		−0.04		−0.03		0.00
	4	0.28		0.23		1.53		−0.03		−0.05		0.01
	Hi	0.51		0.40		1.53		−0.02		−0.09		0.00
Average		0.10		0.01		1.53		0.09		0.04		−0.05

Table A5: Decomposition of Standard HML Beta. Table shows the decomposition of the standard *HML* beta from the three-factor model for 25 size and book-to-market sorted portfolios. The standard beta is decomposed into the cash-hedged beta, ratio of variances, and an adjustment term.

A.6 Figures

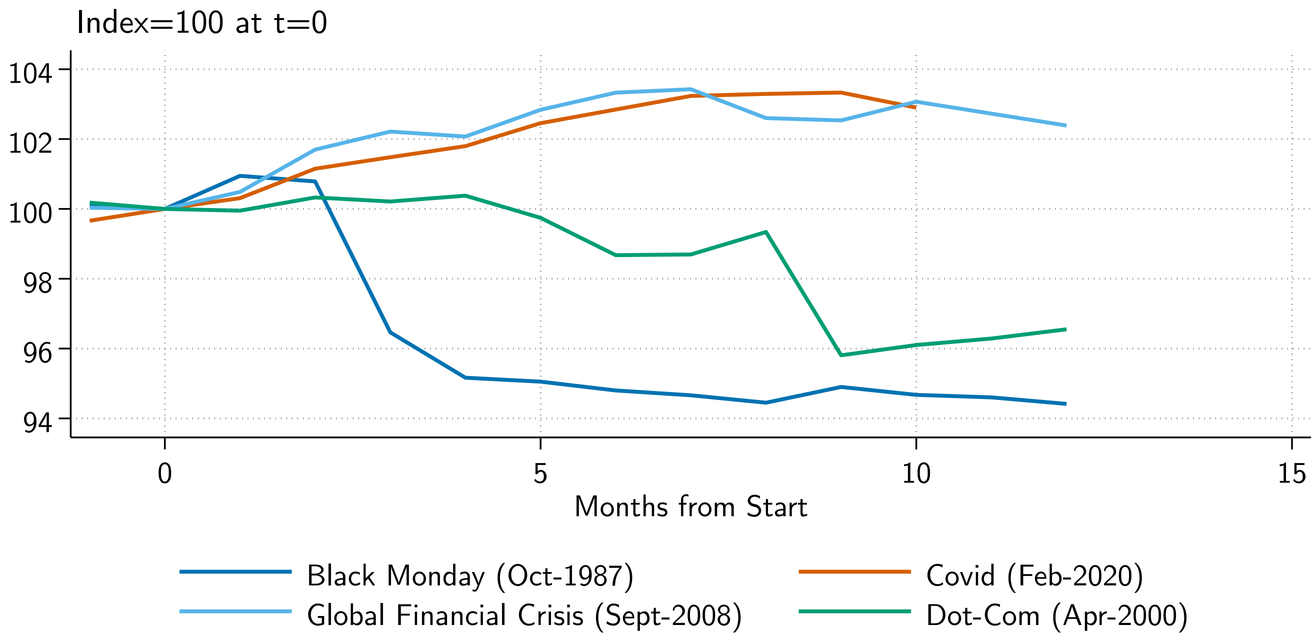

Figure A.1: Average Cash Value During Bad Times. Figure shows the value-weighted value of \$1 during several stress periods. The cash value is indexed to 100 at $t = 0$ defined as: Black Monday (October 1987), Dot-Com bubble (April 2000), Global Financial Crisis (September 2008), and the Covid-19 Pandemic (February 2020).