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Essays in Asset Pricing and Financial Intermediation

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Abstract

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This dissertation consists of three essays on the topics of asset pricing, financial intermediation, and macrofinance.

The first essay shows the role of government risk in asset prices. Firms that depend on the government—either through implicit guarantees or direct sales—face a special risk: government risk. I show that this risk is priced and is not spanned by other factors. I study four cases: U.S. banks, U.S. auto companies, U.S. government suppliers, and Japanese zombie firms. The U.S. cases involve direct exposure to government risk, and a U.S. government risk factor prices portfolios formed from government-dependent firms. Japanese zombies rely on the government's constraints through the intermediary sector, and covariance with government risk drives the intermediary asset pricing result in an environment of loan forbearance.

In the second essay, I show that the effects of regulatory forbearance in Japan confound asset pricing premiums. Japanese zombie firms—companies that receive subsidized credit from banks—arise from regulatory forbearance, and they affect Japanese value and momentum premiums. Controlling for zombies revives the momentum effect in Japan, widely known to be "too low." Zombie-adjusted momentum doubles the unadjusted momentum Sharpe ratio, commands a positive price of risk, and is unspanned by other factors. Value, too, looks more in line with international results. The low momentum effect arises in Japan because of zombies' relationship with their bank lenders. Syndicated loan lending relationships indicate that firms with forbearance-inclined lenders drive low momentum, and zombie losers' high bank beta leads to low momentum returns in strong bank return months.

The third essay, coauthored with Chase P. Ross and Landon J. Ross, studies the effect of firm cash holdings on equity returns. U.S. companies hold cash on their balance sheets, and the share of assets held in cash varies across companies and over time. A firm's cash holdings is an implicit holding in a low-return asset, which pushes down a firm's equity return, and investors should thus hedge out the cash on the balance sheets when calculating equity returns. We show that neglecting to consider cash holdings results in biases in portfolio optimization, factor creation, and cross-sectional asset pricing. We decompose common stock market betas into components, which depend on the portfolio's cash holding, the return on cash, and the portfolio's cash-hedged equity return.

Essays in Asset Pricing and Financial Intermediation

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of
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Dissertation Directors: Gary B. Gorton and Tobias J. Moskowitz

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Dedicated to my parents, Chase, and Grant.

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Chapter 1

Government Risk Exposure

1.1 Introduction

Government dependence takes many forms. In the U.S., government suppliers rely on the government through commercial sales, and banks and auto companies depend on the government's implicit guarantees. In Japan, *zombie* firms count on the government to allow banks to continue evergreening loans. All four types of firms—U.S. government suppliers, U.S. banks, U.S. auto companies, and Japanese zombies—rely on the government's budget capacity. When the government's budget constraint grows more binding, government-dependent firms' returns decrease compared to their less government-dependent peers' returns. Firms with greater government risk exposure have higher expected returns to compensate for bearing government risk.

U.S. government suppliers, large banks, and auto companies rely directly on the government's budget capacity. I show that a U.S. government risk factor prices monthly portfolios of the government-dependent firms and that other factors do not span the government risk factor. In Japan, zombies—companies that receive subsidized credit from banks—are exposed to government risk through the intermediary sector. I show that a Japanese intermediary factor prices zombies because intermediary risk covaries with government risk. In all four cases, government-dependent firms load more on government risk than their counterparts, and the risk exposure increases after the government announces policies that support government-dependent firms.

I proxy for government constraints using a government risk factor constructed from sovereign credit-default swap (CDS) spreads. The government's CDS spread reflects the market's expectation of default. The government risk factor proxies for the shadow price of the government's budget constraint, and the government risk factor reflects the risk that a transfer of taxpayer wealth to a government-dependent firm does not occur. Suppose the need for such a transfer arises: if the government carries a higher default risk, then the associated higher CDS spread reflects a higher financing cost of government interventions, and politicians may be less willing to act. Such wealth transfers—sometimes called bailouts—can occur in many flavors, including capital injections, emergency loans, or lax regulatory oversight, but ultimately, bailouts require government resources. The government must have the budget capacity to execute the transfer.

I separate my results into three parts. First, government risk determines the expected returns of U.S. government-dependent firms. I form size-and-book-to-market portfolios from government suppliers, large banks, and auto companies separately. I show that a U.S. government risk factor prices the portfolios.

Second, I conduct event studies to show that government-dependent firms have greater government risk exposure than other firms. Government suppliers rely on the government to translate taxpayer funding into purchase orders, and a budget-constrained government may cut orders. Firms with sales to the federal government are most likely to be affected by government belt-tightening, and I show that government suppliers face lower abnormal returns than non-suppliers after the 2011 U.S. sovereign debt downgrade.

Banks and autos derive their dependence from support announcements by the government. Large U.S. banks were viewed as *too big to fail* starting in the 1980s, and auto companies received federal bailouts in the Global Financial Crisis. Both groups rely on the government's implicit support of bailouts in bad states, and large banks and automakers have higher betas to the government's constraints after implicit and explicit bailout announcements.

Last, I examine zombies in Japan. Beginning in the 1990s, Japanese banks restructured loans to insolvent borrowers—zombie firms—to avoid recognizing non-performing loans and their associated capital write-down. Banks rolled over loans many times in an environment of regulatory forbearance and implicit government support. Zombies rely on the government to continue supporting forbearance, and the support exists through the intermediary sector.

The intermediary factor prices zombie firms sorted into 25 size-and-book-to-market portfolios. I decompose the intermediary factor into two components: a part driven by government risk and a part orthogonal to government risk. The component of intermediary risk correlated with government risk drives the intermediary pricing of zombies. Non-zombies are not dependent on the government and are not priced by the same component.

Zombie firms differ from bank-dependent firms in their government dependence, and the difference is reflected in asset pricing tests. I classify firms as bank dependent using three measures: external-finance dependence, bank beta, and whether the firm finances itself through long-term debt issuance. I form bank-dependent portfolios, and I show that the overall intermediary factor also prices bank-dependent portfolios, but the component of intermediary risk that is unrelated to government risk drives the result.

Outside of Japan and the U.S., banks and government risk are closely linked. Unlike virtually all other industries, banks are widely believed to have recourse to the government purse in bad states, given the negative externalities of bank failures and financial instability. I use Fitch bank support ratings for international banks to show that banks with a higher probability of government support have greater domestic government risk exposure.

The relationship between the government's budget capacity and firms' returns is salient in the wake of the COVID-19 pandemic. The U.S. government's unprecedented mobilization supplied $2.6 trillion—12.6% of GDP—in discretionary fiscal easing, excluding automatic stabilizers and loan guarantees. In Europe, the European Central Bank unveiled the $1.5 trillion Pandemic Emergency Purchase Program to buy public and private securities. Investors worldwide spent considerable resources reading the tea leaves of if or when governments would backstop national champions. To name only a few: American Airlines, Lufthansa, Air France, KLM, and Renault all received some form of unusual government aid during the pandemic. Whether investors view COVID-19 as reshaping the likelihood of future government intervention in bad times or as a 100-year flood with a proportionate government response, the role of government risk in financial markets will be first-order important for the near future.

Section 3.4 describes the data and factor construction. Section 1.3 shows the cross-sectional pricing results for U.S. government-dependent firms and U.S. event studies. Section 1.4 presents the Japanese intermediary asset pricing results. Section 3.6 concludes.

Related Literature

This paper builds on earlier papers that study the role of government involvement in financial markets. Cohen and Malloy (2016) show that firms with a commercial sales relationship with the government become less competitive than their industry peers because the government-dependent firms invest less in physical and intellectual capital. Gandhi and Lustig (2015) show that the largest commercial bank stocks have lower risk-adjusted returns than smaller bank stocks because the largest bank stocks have government guarantees. Belo et al. (2013) measure government exposure as the proportion of the industry's total output using the NIPA input-output data and show that firms are priced by exposure to the government sector conditional on the presidential party in power. Dissanayake (2019) prices the cross-section of asset returns using shocks to government defense spending to create a factor-mimicking portfolio.

I construct a government risk factor from sovereign CDS spreads, a high-frequency market price that measures the expensiveness to finance government spending or the capacity of government spending, rather than the amount of realized government spending. Chernov et al. (2020) show that U.S. sovereign CDS premiums reflect the endogenous risk-adjusted probabilities of fiscal default. Using sovereign CDS spreads also incorporates political uncertainty risk, which commands a risk premium in equity option markets (Kelly et al., 2016) and a larger risk premium in a weak economy (Pastor and Veronesi, 2013).

This paper also contributes to the literature on zombie credit. In Japan, the lost decade of the 1990s turned into more than two lost decades because of low productivity growth (Hayashi and Prescott, 2002). Underlying the productivity problems were zombies. Japanese banks evergreened loans to weak firms to avoid losses on their bank balance sheets, with more troubled firms more likely to receive bank credit (Peek and Rosengren, 2005). Caballero et al. (2008) show that zombies have negative externalities for healthy firms because zombies reduce the profits of healthy firms and lower investment and employment growth for non-zombies. Zombies had large macro effects on Japan's productivity growth and altered the competitive process.

Zombies are not unique to Japan. Andrews et al. (2017) document an increase of zombie firms in OECD countries since the mid-2000s, and they show that the zombies' survival attenuates labor productivity growth. Banerjee and Hofmann (2018) show a rise of zombies in 14 advanced economies since the late 1980s, and they attribute the increase to reduced financial pressure in the form of lower interest rates. Acharya et al. (2020) show how zombie credit has a disinflationary effect by creating excess production capacity, increasing supply, and lowering prices. Schivardi et al. (2019), Bonfim et al. (2020), and Blattner et al. (2019) show the role of bank lending relationships to zombie firms in Italy and Portugal.

My paper relates to the literature on intermediary asset pricing, in which financial intermediaries are the marginal investors. When intermediaries' balance sheet capacity declines and intermediaries face tight funding constraints, intermediaries have a high marginal utility of wealth. Assets that do not pay off in bad states are considered risky and must have a higher expected return to compensate for the risk. Brunnermeier and Pedersen (2009) show how funding liquidity enters the pricing kernel and use leverage to proxy for funding conditions. He and Krishnamurthy (2012) create a model in which low intermediary capital decreases the marginal investor's risk-bearing capacity. He and Krishnamurthy (2013) model risk premiums during crises.

Empirical work supplements the theory of intermediary asset pricing. Adrian et al. (2014) show that shocks to the leverage of securities broker-dealers price equity and bond portfolios. He et al. (2017) construct a factor of shocks to the equity capital ratio of primary dealers. They show that the capital ratio factor prices portfolios of corporate bonds, sovereign bonds, derivatives, commodities, and currencies.

1.2 Data

U.S. Data I use CRSP return data and Compustat annual financial statement data. I follow Fama and French (1992a) to merge the return data and accounting data. In this way, I match accounting data in calendar year $t-1$ with return data for July t to June $t+1$ to give a 6-month minimum gap between the fiscal year-end and the return data.

I use the Compustat Segments dataset to calculate a firm's government sales ratio—the percent of sales to the U.S. government—on an annual basis. Firms are required to report operating segments that represent more than 10% of revenues and customers that make up more than 10% of total reported sales in their financial reports under Statements of Financial Accounting Standards (SFAS) 131.[1] Firms classify customers as one of seven customer types: company, geographic region, market, state government, local government, domestic government, or foreign government. I calculate the government sales ratio as the sales to the U.S. domestic government as a fraction of total sales for each company and year.[2] The Compustat Segments data began in 1976.

Japanese Data I use Japanese market data and accounting data from Datastream and Worldscope. The data cover 1979 to 2018 and consist of the universe of Japanese stocks in Datastream and Worldscope. I restrict my sample to companies with a book value in the previous six months and at least 12 months of return history, and I exclude financials (including REITs) and stocks that have a share price less than $1 at the start of each month.

Similar to Asness et al. (2013a), I restrict the data to a sample of liquid stocks. Each month, I sort stocks by market capitalization in descending order. Starting with the largest market capitalization stock, I include all stocks until the cumulative market capitalization is 90% of the total market capitalization for that month.

Identifying Zombies I identify zombies following Caballero et al. (2008): I compare a firm's actual interest payment, $R_{i,t}$, to an estimated lower-bound $R^{\star}_{i,t}$. The lower-bound stands for the interest payments a firm i could expect if it borrowed at no spread to the prime rate at time t:

$$R^{\star}_{i,t} = r^{s}_{t-1} S_{i,t-1} + \left(\frac{1}{5} \sum_{j=1}^{5} r^{\ell}_{t-j} \right) L_{i,t-1} \tag{1.1}$$

where $S_{i,t}$ is short-term debt and $L_{i,t}$ is long-term debt, and r^{s}_{t} and r^{ℓ}_{t} are the Bank of Japan's short-term and average long-term prime rates, which reflect the prime lending rate at which principal banks lend.

I construct the interest-rate gap, $X_{i,t}$, as the difference between the actual interest payment and the lower bound, scaled by the total debt:

$$X_{i,t} \equiv \frac{R_{i,t} - R^{\star}_{i,t}}{B_{i,t-1}} = r_{i,t} - r^{\star}_{i,t}. \tag{1.2}$$

[1]Before 1997, Financial Accounting Standards Board (FASB) No. 14 required firms to report the data.

[2]I exclude sales labeled as sales to the domestic government but have a customer name linked to foreign domestic governments and agencies (e.g. "Brazilian Air Force" or "Canadian Government").

In principle, only the highest-quality companies should borrow at effective rates near the prime rate, and most corporate borrowers would expect to borrow at a nontrivial spread to the prime rate. Following Caballero et al. (2008), I define companies with an interest-rate gap below 0 as *crisp* zombies, and companies borrowing near the prime rate—those with an interest-rate gap of 0 to 50 bps—as *fuzzy* zombies. I lag the interest-rate gap by six months to match the accounting data lag and ensure the balance sheet data are in the investors' information set.

Zombies-ness is persistent, and switches from zombie to non-zombie or vice versa occur roughly 1.5% of the time. The interest-rate gap is uncorrelated with firm size. Before removing small and illiquid stocks to restrict the sample to a liquid sample, size has a correlation of −0.1% with the interest-rate gap, a correlation of 4.8% with an indicator for crisp zombie, and a correlation of 3.8% with an indicator for crisp or fuzzy zombie. Cleaning the dataset to the liquid set of stocks increases the share of zombies from 20% to 48%.

Government Risk Factors I derive my measure of government risk using the sovereign credit-default swap (CDS) spread. A CDS swaps credit risk of the reference entity, which can be either a private entity or a sovereign. Investors that buy sovereign CDS buy insurance from credit events such as a missed coupon payment, a default, or a debt restructuring. The CDS spread reflects the market's expectation of default, and issuers with higher CDS spreads face higher financing costs. All else equal, governments with higher CDS spreads will face higher financing costs should the sovereign turn to markets to finance an intervention.

I construct each country's government risk factor using innovations to the sovereign CDS spread from an AR(1) regression:

$$SovereignCDS_t = \rho_0 + \rho_1 SovereignCDS_{t-1} + u_t. \tag{1.3}$$

I convert the innovation into a growth rate by dividing by the lagged CDS spread

$$GovFac_t = -1 \times \frac{u_t}{SovereignCDS_{t-1}}, \tag{1.4}$$

and I multiply by −1 so that $GovFac_t$ decreases when the government is constrained. The U.S. factor is $GovFac$, and the Japanese factor is $GovFac_{JP}$. I create the factor following a method analogous to He et al. (2017). As expected, the U.S. government risk factor is correlated with news-implied and financial-statement-implied measures of government risk from other papers. See Appendix 1.8.1 for details.

The CDS data are from Markit and begin in 2002, with U.S. sovereign CDS data are available starting in 2003. Since the too big to fail event occurred in 1984, I form a synthetic U.S. sovereign CDS spread using the par-equivalent CDS spread approach, an industry standard and described in Beinstein and Scott (2006). See

Appendix 1.8.1 for details. I use innovations to the synthetic U.S. sovereign CDS spread and Equations 1.3 and 1.4 to create the synthetic U.S. government risk factor, $GovFac_{synthetic}$.

Intermediary Risk Factors in Japan I construct Japanese versions of the two quarterly intermediary factors in Adrian et al. (2014) and He et al. (2017). Adrian et al. (2014) use shocks to intermediary leverage to construct the risk factor *LevFac*. I use the balance sheet data of financial dealers and brokers to form the Japanese leverage factor, $LevFac_{JP}$. The data come from Japan's Flow of Funds and begin in 1998.

He et al. (2017) use innovations to intermediary capital ratios to form a risk factor, which I will call *CapFac*. I construct the Japanese capital ratio factor, $CapFac_{JP}$, from members of the "Japanese Government Bond Market Special Participants Scheme." The program began in October 2004 and mirrors the U.S. primary dealer system. I manually map the members to holding companies following He et al. (2017)'s approach. I use book debt and market equity data from Datastream to construct the intermediary capital ratio.

1.3 Direct Government Dependence

In the U.S., government suppliers, large banks, and auto companies rely directly on the federal government. Government suppliers have a commercial sales relationship with the government, and they rely on the government to translate taxpayer dollars into purchase orders. Big banks and automakers are government dependent through implicit guarantees: the largest banks are considered too big to fail; auto companies received bailouts in the Global Financial Crisis and highlight that the American-ness of a company or the political value of their employees' jobs might lead some companies to be more government-dependent. I show the relationship between government risk and firms' returns using cross-sectional asset pricing tests, event studies, and international evidence.

1.3.1 U.S. Cross-Sectional Regressions

If government risk reflects when the government is constrained, then government-dependent firms with greater risk exposure should have higher expected returns to compensate investors for bearing government risk. I test this hypothesis.

I show that the U.S. government risk factor, *GovFac*, explains the cross-section of expected returns for portfolios of U.S. government-dependent firms. I form monthly portfolios of three sets of government-dependent firms, double-sorted on size and book-to-market. First, I construct 25 portfolios of U.S. government suppliers. Government suppliers are firms with at least 10% of their annual sales to the U.S. government. Second, I form six portfolios of the largest 50 U.S. banks. Third, I form six portfolios of U.S. automakers. All portfolio returns are value-weighted. Event studies in Section 1.3.2 support my classifications of government-dependent firms.

I calculate the price of risk for a risk factor using the portfolio returns and a two-step procedure. First, I estimate each portfolio i's beta to the risk factor using time-series regressions of each portfolio's excess return on the factor:

$$R^e_{i,t} = \alpha_i + \beta'_{i,f}\mathbf{f}_t + \varepsilon_{i,t},\ i = 1, \ldots, N,\ t = 1, \ldots, T, \tag{1.5}$$

where $\mathbf{f}_t$ is a vector of risk factors. Then I run a cross-sectional regression of portfolio excess returns on the betas estimated in Equation 2.9:

$$\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f + \xi_i,\ i = 1, \ldots, N. \tag{1.6}$$

Using $\mathbf{f}_t = GovFac_t$ and the two-step procedure gives the government risk factor's price of risk, λ_{GovFac}.

Table 1.1 shows the prices of risk from the cross-sectional regressions and GMM t-statistics. The first three columns show the price of risk estimates, pooling all the portfolios and imposing the same price of risk across them. I restrict the portfolios to those with data for 80% of the full period. In the cross-sectional regression, the government risk factor commands a positive and significant price of risk for the government-dependent portfolios. The coefficient of 0.41 means that a portfolio with $\beta_{GovFac} = 1$ carries an annualized expected return of 0.41%. Increasing the portfolio's β_{GovFac} by one standard deviation increases the annualized expected risk premium by 3.7 percentage points (PP), and the risk compensation for *GovFac* is economically large. Columns 2 and 3 show similar results with the market, size, and value factors included.

In the next three columns, I show that the government risk factor prices the cross-section of portfolios formed from government suppliers. The risk factor earns a positive and significant price of risk, and a one standard deviation increase in beta corresponds to a 4.8PP increase in risk premium. The GRS p-value from the time-series regressions is large, consistent with failing to reject the model. The results are robust to adding the market, size, and value factors to the model. Including these factors increases the time-series R^2 and lowers the mean average pricing error.

In the last four columns, I use the traditional Fama–French 25 size-and-book-to-market portfolios. I show that *GovFac* is not a compensated source of risk for the Fama–French portfolios. The results show that the standard 25 portfolios are sorted in a way that yields no heterogeneity in government risk exposures across the portfolios. In column 9, the size and value factors do not price the Fama–French portfolios because the regression is constrained to months where *GovFac* is available; column 10 shows that value has a positive price of risk using data that starts in July 1926.

While Table 1.1 uses estimated betas, I can instead run two separate firm-level cross-sectional regressions using the government supplier characteristic. First, I test expected returns on an indicator of whether a company is a government supplier:

$$\mathbb{E}[R^e_{i,t}] = \gamma_0 + \gamma_1 \mathbb{I}(\text{Government Supplier}) + \xi_i. \tag{1.7}$$

Second, I test expected returns on the government sales ratio, which measures the intensity of a firm's government dependence:

$$\mathbb{E}[R^e_{i,t}] = \gamma_0 + \gamma_1 (\text{Government Sales Ratio}) + \xi_i. \tag{1.8}$$

Table 1.2 shows the results from the two characteristic-based cross-sectional regressions. In the cross-section, government suppliers have higher returns than non-suppliers, and the intensity of government dependence corresponds to higher returns. The first two columns test the indicator setup and find that government suppliers' returns are 0.20PP higher on average than non-government suppliers. Since this test looks across all firms, rather than testing within suppliers, the large and significant intercept shows that non-suppliers also have positive returns. The last two columns use the intensity of the government sales ratio instead of the indicator and find a similar result. Controlling for firm size and book-to-market does not materially change the results.

In Table 1.3, I show that other factors do not span the government risk factor, meaning the other factors do not contain *GovFac*'s economic content. The U.S. government risk factor is also not spanned on a daily or quarterly level. In the first column, I regress *GovFac* on the standard Fama–French factors and find that the government risk factor is weakly correlated with the market and *HML*, but neither is significant. Notably, *GovFac* is not spanned by any of the factors, as shown by its large and significant intercept.

The combined results show that firms exposed to government risk earn compensation for the risk of lower returns when the government becomes constrained. But government risk exposure matters only for a subset of firms: returns of non-government-dependent firms are less dependent on the government's constraints, and the factor does not describe the cross-section of Fama–French portfolios.

1.3.2 U.S. Event Studies and International Evidence

If a firm is government dependent, and that dependence is risky, then the firm's returns will covary with innovations to government risk, and the firm will have lower returns after adverse shocks to government risk.

I test these hypotheses.

First, I show that government-dependent companies' realized returns have higher beta to a U.S. government risk factor than the returns of their less government-dependent counterparts. Second, I use event studies to study government-dependent companies' returns after shocks to government risk. I show that when the government's budget constraint grows more binding, government-dependent firms have lower returns. After the 2011 U.S. sovereign debt downgrade—a period when government risk increased—government suppliers had lower returns than non-suppliers. After announcements of government support—such as the explicit introduction of the too big to fail concept—large banks and auto companies had higher beta to government risk.

Government risk is not unique to the U.S.; internationally, bank returns rely—often implicitly—on government support. Governments are motivated to avoid bank failures because financial instability has large negative externalities, and bank returns depend on the government's capacity to support banks if bailouts are needed. I show that a higher likelihood of external support measured by the Fitch bank support ratings corresponds to greater dependence of banks' loadings on their home country's government risk factor.

Government Suppliers

I systematically measure a firm's government dependence by its sales to the U.S. government. I calculate each firm's annual government sales ratio as the percent of sales to the U.S. government. I consider firms with an annual government sales ratio of at least 10% to be government suppliers. I define firms with no government sales reported or a government sales ratio of less than 10% as non-suppliers. Specifically, if a company discloses no government sales, then the federal government accounts for less than 10% of that firm's sales that year. Table 1.4 shows examples of firms in each group. Prominent government suppliers span many industries; unsurprisingly, defense contractors like Raytheon and Northrop Grumman have high government sales ratios, but less obvious examples include Aetna, Con Edison, Corrections Corporation of America, and Walgreens. Non-suppliers span many industries as well: Amazon, Coca-Cola, Microsoft, and Walmart. In other words, sorting on government suppliers is not just a defense industry effect.

I show that government suppliers have greater government risk exposure than non-suppliers. Consistent with my prediction that government risk is a priced risk, I show that the government sales ratio covaries with beta to the U.S. government risk factor. First, I calculate daily value-weighted portfolios for suppliers and non-suppliers and regress the portfolios' returns on the government risk factor. Table 1.5 column 1 shows that a portfolio long government suppliers and short non-suppliers significantly covaries with innovations to government risk, as predicted. Columns 2 and 3 show the long and short legs separately: while both significantly covary with government risk, the beta for government suppliers is thirty times larger than the beta for non-suppliers. The covariance of the non-suppliers portfolio with government risk isn't surprising: my definition of non-suppliers likely mixes some companies that have government sales rates just below the 10% disclosure threshold with companies that have a 0% ratio. Even if I had perfect insight into companies with no commercial relationship with the government, there are likely second-order effects—such as suppliers of suppliers—that have links to suppliers, so it's not clear the non-suppliers portfolio should have zero covariance with government risk.

Digging deeper, Figure 1.1 presents a scatterplot of beta to the government risk factor against the government sales ratio for each industry. The corresponding regression has a positive and significant coefficient, showing that industries with higher government sales ratios also have greater government risk exposure.

U.S. Sovereign Debt Downgrade When government risk increases, government-dependent firms' returns should reflect that increased risk. I compare the returns of government suppliers and non-suppliers after the U.S. sovereign debt downgrade on August 5, 2011, when the S&P cut their rating for U.S. sovereign debt. S&P cut the credit rating after political disagreement surrounding the debt ceiling increase in July 2011 and a budget deal passed in early August that the S&P felt "falls short of what, in our view, would be necessary to stabilize the government's medium-term debt dynamics." The rating was cut one notch, from "AAA" to "AA+ with a negative outlook," in the first-ever downgrade to the U.S. government's long-term credit rating. The ratings-cut dominated headlines, and markets responded immediately: the ratings-cut announcement came after markets closed on Friday, and the S&P 500 dropped 6.7% on Monday.

I study cumulative abnormal returns compared to a CAPM model. I use daily data before August 5, 2011, and regress the return of each firm i on the market return:

$$R_{i,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \varepsilon_{i,t}. \tag{1.9}$$

I use the estimated coefficients to calculate each firm's predicted returns, $\hat{R}_{i,t}$, and I calculate the abnormal return, $AR_{i,t}$, as the difference between the realized and predicted return:

$$AR_{i,t} = R_{i,t} - \hat{R}_{i,t}. \tag{1.10}$$

Figure 1.2 plots the cumulative abnormal return for government suppliers and non-suppliers in the week after the downgrade. On August 8—the first trading session after the downgrade—government suppliers and non-suppliers both had large negative abnormal returns. But government suppliers faced a significantly larger drop, and their cumulative abnormal returns were lower over the next week, consistent with my hypothesis that government-dependent firms have greater exposure to government risk.

Banks

My second group of government-dependent companies consists of large banks. Unlike virtually all other industries, banks are widely believed to have recourse to the government purse in bad states, given the negative externalities of bank failures and financial instability. I show that banks are government dependent in two ways: first, I perform an event study around the announcement that some U.S. banks were too big to fail. In 1984, amid the bailout of Continental Illinois, regulators acknowledged that the largest banks were too big to fail. Following the event, government risk exposures increased for the largest banks, and when the government becomes constrained, the largest commercial banks have lower returns than other commercial banks. Second, I show that banks *globally* depend on their home government: I use Fitch bank support ratings for international banks to show that banks with a higher probability of government support have greater domestic government risk exposure.

Too Big to Fail On September 19, 1984, the Comptroller of the Currency testified before the House Banking Committee on the $4.5 billion rescue of Continental Illinois; at the time, Continental Illinois was the largest bank failure in U.S. history. During his testimony, the Comptroller acknowledged that some banks were too big to fail and said this policy applied to the 11 largest banks. The Comptroller did not name the banks, and the Dow Jones Broad Tape did not initially mention too big to fail (O'Hara and Shaw, 1990). The next day, however, *The Wall Street Journal (WSJ)* published a list of the 11 largest banks based on year-end 1983 assets, drawing considerable attention to the initially-overlooked event. The *WSJ* event made banks' implicit support explicit and common knowledge, and it categorized banks into two groups: too big to fail versus too small to save.

After the event, the 11 affected banks had greater government risk exposure: when the government becomes more fiscally constrained, the returns of the 11 named banks decline. I regress each commercial bank i's returns on the synthetic U.S. government risk factor, and the factor interacted with indicators for being in the treatment group of the 11 banks cited in the *WSJ* article, after the *WSJ* article was published, and both.

$$
\begin{aligned}
R_{i,t} = \alpha \\
&+ \beta_1 \, GovFac_{synthetic,t} \\
&+ \beta_2 \, GovFac_{synthetic,t} \times \mathbb{I}(\text{WSJ}) \\
&+ \beta_3 \, GovFac_{synthetic,t} \times \mathbb{I}(\text{Post}) \\
&+ \beta_4 \, GovFac_{synthetic,t} \times \mathbb{I}(\text{WSJ}) \times \mathbb{I}(\text{Post}) + \varepsilon_{i,t}
\end{aligned}
\tag{1.11}
$$

where i is a commercial bank, t is a day, $\mathbb{I}(\text{Post})$ is an indicator for after the event, and $\mathbb{I}(\text{WSJ})$ is an indicator for the 11 banks cited by the *WSJ*.

Table 1.6 shows the regression results for commercial banks and for the top 50 commercial banks. When the government becomes constrained and $GovFac_{synthetic}$ decreases, commercial bank returns decline on average (columns 1 and 6). The coefficient of 0.007 translates to a 2pp decrease in return for a one standard deviation decrease in $GovFac_{synthetic}$ on an annualized basis.

The *WSJ* banks have higher beta to government risk than other commercial banks. The too big to fail banks have more than quadruple the government risk exposure of other commercial banks and more than triple the exposure of other large commercial banks (columns 2 and 7). The coefficient for the risk factor interacted with both indicators, β_4, is positive and significant. After the event, the 11 *WSJ* banks have greater government risk exposure. Moreover, after the event, banks that were not one of the treated 11 banks had lower beta. This result is consistent with investors initially believing large banks were, in general, dependent on the government, and then updating their beliefs after the event separated banks that could expect extraordinary support from banks that could not.

Figure 1.3 plots the beta to the synthetic government risk factor for the 11 *WSJ* banks and the beta of the next two largest banks: Mellon Bank and Crocker National Bank. After the event, the government risk beta for the 11 *WSJ* banks jumped up. Meanwhile, the next two largest banks remained steady in their government dependence.[3] Appendix 1.8.2 shows robustness results, including adding controls, using a placebo event date, and restricting the banks to large banks near the too big to fail policy cutoff.

Bank Support Ratings An issuer's credit rating measures the borrower's creditworthiness—its capacity to repay its financial obligations. But for banks specifically, rating agencies regularly publish two different ratings: one that reflects the bank's creditworthiness *with* government support, and one *without* government

[3] Mellon Bank and Crocker National Bank are the next two largest banks. They are the 13th and 14th largest banks because First Interstate Bancorp is ranked 7th, consistent with news articles, but not included in the *WSJ* article. Crocker merged with Wells Fargo in 1986.

support. The existence of such ratings reinforces the close connection between banks and the government.

I examine Fitch's bank support ratings. Fitch Ratings' support rating assesses the likelihood that a bank receives external support—that is, government assistance—if it runs into significant financial difficulties. The support rating puts a minimum bound on the long-term rating, and the support rating ranges from 1 to 5. A bank with an "extremely high probability of external support" has a support rating of 1, and a bank with "a possibility of external support, but it cannot be relied upon" has a support rating of 5. The support rating does not assess the bank's intrinsic credit quality and reflects only whether the rating agency thinks a bank would receive support if needed. The support rating is available for many banks internationally and puts a floor on the bank's long-term rating; banks with a support rating of 1 have a minimum long-term rating floor of A−.

I show that a higher probability of external support corresponds to greater government risk exposure for banks worldwide. The logic is straightforward: suppose investors expect that a bank can, in bad states, expect a backstop from its home government. Now, suppose the market's belief of that government's riskiness increases. If the government decides to finance a bank intervention, all else equal, the government will face higher borrowing costs, meaning the intervention is either less likely or offered with worse terms. In either case, bank shareholders are worse off.

To test the hypothesis, I use the members of the Bloomberg Banks Index, which includes 156 leading global bank stocks from 43 countries. Of the 156 banks, 130 have Fitch support ratings. Figure 1.4 shows each country's average Fitch support rating and the number of ratings included in the average. For example, all three Japanese banks in the index have an "extremely high probability of external support," consistent with Japan's long history of government support of forbearance. Banks in other developed market countries cannot rely as much on external support, and all 19 U.S. banks in the index have a support rating of 5. Emerging market countries have a higher probability of external support. China's 25 banks have an average support rating of 1.7: 12 banks have a support rating of 1, and none have a support rating over 3.

Figure 1.5 plots the bins of countries' support rating against bank beta to the country's government risk factor, where I calculate the government risk factors in an analogous method as for the U.S.-based *GovFac* described previously. I calculate each beta by regressing the bank's daily return against the one-day lag of the relevant country's government risk factor during the pre-crisis period. A higher beta to government risk shows greater dependence on government risk and corresponds to a higher probability of external support, and the corresponding regression shows a significant relationship.

Auto Companies

My third category of government-dependent firms is auto companies. Auto companies are government dependent for many reasons: they are politically important and often seen as national champions, they are large and salient employers, and they can manufacture equipment for national security. Their implicit government backstop became explicit during the Global Financial Crisis when U.S. automakers received extraordinary support. The announcement of explicit government support for the largest auto companies created a new dependence on the government. After the announcement, auto returns increased their government risk exposure, as measured by beta to the actual government risk factor, compared to non-auto companies.

On October 3, 2008, the United States Congress passed the Emergency Economic Stabilization Act of 2008. The legislation created the Troubled Asset Relief Program (TARP), which funded many crisis interventions, including the Capital Purchase Program for bank equity purchases and Term Asset-Backed Securities Loan Facility (TALF). On December 19, 2008, the U.S. Treasury unveiled the Automotive Industry Financing Program. The program used nearly $80 billion of TARP funds to support the auto industry. The program rescued GM and Chrysler, two of the *Big Three* U.S. automakers.

Combined, Klier and Rubenstein (2012) estimate that GM received $50.2 billion in financial aid through TARP, GMAC (and Ally) $17.2 billion, Chrysler $10.9 billion, and Chrysler Financial $1.5 billion across the Bush and Obama administrations. Ford, the other member of the Big Three, avoided a TARP bailout since it had obtained a large line of credit a year ahead of the crisis. But Ford used the TALF and the Commercial Paper Funding Facility, and public perception of Ford differed little from that of GM and Chrysler. Ford's stock price dropped alongside GM's and Chrysler's, and Ford's CEO went with the CEOs from GM and Chrysler to request emergency aid from the Congress in November 2008 (Klier and Rubenstein, 2012).

I compare the returns of the Big Three automakers against the returns of a control group of non-auto non-commercial bank firms. I exclude commercial banks from the control group because I showed their government dependence in section 1.3.2. I use the method from equation 1.11. Table 1.7 shows the result. Columns 2 and 7 show that automakers have greater government risk exposure than the control group in general: for example, the average control group firm has a government risk beta of 0.7, while the betas of the Big Three autos are almost double that at 1.3. Column 5 presents the full result. After the government support announcement, the beta to government risk increases by 1.6 for the Big Three. After the bailout announcement, when the government's constraints tighten, automakers' returns decline more than other companies.

Figure 1.6 shows the beta to the U.S. sovereign risk factor for auto companies and the control group.

Before December 19, 2008, auto companies had a negative beta to the U.S. government risk factor. After the bailout announcement, the beta turned positive and increased more sharply than the control group's beta. See Appendix 1.8.2 for robustness and more analysis.

1.4 Intermediated Government Dependence

I now move from examining cases of *direct* government dependence to *intermediated* government dependence. I study Japan, given the existing work that documents the country's unique zombie history—in this context, Japan is the extreme example, but I expect similar effects anywhere the government condones zombies. Figure 1.7 shows widespread zombies in Japan: in recent years, nearly half of my sample is considered a zombie.[4]

In Japan, zombies rely on the government through the intermediary sector. Zombies depend on banks to continue evergreening their loans, and zombies depend on the government to continue allowing forbearance. The government faces a budget constraint and can allocate only so many resources toward forbearance or subsidized credit. I show that zombies' government dependence through the intermediary sector is reflected in their pricing.

I find that Japanese intermediary risk factors price zombie portfolios, and I posit that the intermediary factor is a function of government risk as long as the government condones continued forbearance. I split the intermediary risk factor into two parts—one correlated with government risk, the other orthogonal to government risk. The government risk component drives the intermediary pricing of the zombie portfolios.

Zombies are not just bank-dependent firms. Zombies differ from bank-dependent companies in their government dependence: zombies are both bank dependent and government dependent. To test the difference between bank dependence and government dependence, I try to price the bank-dependent portfolios using the intermediary factor and its components. Bank-dependent portfolios are priced by intermediary risk (like zombies) because they are priced by the orthogonal component (unlike zombies). These results, combined with the zombie portfolios' pricing results, show that the difference between bank dependence and government dependence is reflected in pricing.

Figure 1.8 summarizes the asset pricing results for zombie and bank-dependent portfolios. The intermediary factor prices both, but for distinct reasons. Zombies rely on the government through the intermediary sector; the government risk component of intermediary risk prices zombie portfolios because zombies' expected returns reflect the riskiness of whether assets will pay off in bad states as determined by the tightness of the

[4] The fraction of zombie firms in my dataset is similar to the percent from Caballero et al. (2008), which uses Nikkei Needs data.

government's constraints. Bank-dependent firms are not differentially affected by the government's capacity, and they face intermediary risk unrelated to government risk.

1.4.1 Cross-Sectional Regressions

I split my sample of Japanese companies into two buckets, zombies and non-zombies. For each bucket, I construct 25 size-and-book-to-market portfolios. The portfolios are quarterly to match the intermediary factor's frequency and are value-weighted. I form portfolios using 98% of the market capitalization (rather than 90%). Using 90% of the market capitalization gives similar price of risk results, but the number of observations is occasionally considerably lower. I use the two-step procedure in Equations 2.9 and 2.10 and the intermediary factor, $\mathbf{f} = \mathit{LevFac}_{JP}$, to calculate the intermediary factor's price of risk.

Table 1.8 shows the price of risk from cross-sectional regressions using a single factor model. The intermediary leverage factor, LevFac_{JP}, explains the cross-section variation of zombie portfolios but does not price non-zombies or Fama–French portfolios. The results are robust to using the capital ratio factor instead of the leverage ratio factor, adding a market factor, and including the ten momentum portfolios. Unlike the U.S., the Japanese leverage and capital factors are negatively correlated, and they have opposite price of risk signs. I discuss the signs in detail in Appendix 1.8.3.

I use the intermediary leverage factor to calculate the predicted returns for the zombie and non-zombie portfolios, and I plot the realized returns against the predicted returns in Figure 1.9. For zombie portfolios, predicted and realized returns line up near the 45-degree line. For non-zombies, the predicted returns cluster in a small range, while realized returns spread over a broader range, reflecting the failure of the intermediary factor to price non-zombie portfolios.

The cross-sectional results show that zombie returns are differentially affected by banks' ability to take on leverage. Bad times for banks are worse for some zombies. As described in Adrian et al. (2014), the intermediary stochastic discount factor (SDF) is a negative function of the leverage factor. Times of low leverage—when banks are lending less per yen of equity—correspond to times of high marginal utility for intermediaries and low returns for the riskiest firms. To compensate for low returns in bad times, these zombies have high expected returns. Other zombies have strong returns in bad times, so they serve as a good hedge and have lower expected returns. For non-zombies, the covariance of returns with the intermediary SDF is not informative for expected returns.

Zombies' dependence on the government manifests through the intermediary sector. Under forbearance, Japanese intermediary risk and government risk are correlated. Japanese broker-dealer leverage and sovereign CDS are 66% correlated in level terms, and their log changes have a 44% correlation. I show that the correlation between intermediary risk and government risk leads to the zombie intermediary asset pricing result.

I split the intermediary factor into two parts: a component correlated with the government risk factor, $LevFac_{predicted}$, and an orthogonal component, $LevFac_{residual}$. I regress the Japanese intermediary factor on the Japanese government risk factor:

$$LevFac_{JP,t} = \underbrace{\alpha + \beta GovFac_{JP,t}}_{LevFac_{predicted,t}} + \underbrace{\varepsilon_t}_{LevFac_{residual,t}} \tag{1.12}$$

$LevFac_{predicted}$ is the predicted dependent variable. $LevFac_{residual}$ is the regression residual. I use the two components of $LevFac_{JP}$ to price portfolios following the two-step procedure in Equations 2.9 and 2.10 and $\mathbf{f} = LevFac_{predicted}$ and $\mathbf{f} = LevFac_{residual}$, separately, to calculate the prices of risk.

Table 1.8 shows that $LevFac_{predicted}$ prices zombie portfolios and drives the intermediary asset pricing of zombie portfolios. The orthogonal component, $LevFac_{residual}$, does not explain the cross-sectional variation of zombie returns; and in a horse-race of the two components, the predicted components have larger t-statistics. Zombie portfolios are differentially exposed to the risk that the government will no longer support forbearance, and government risk underlies the intermediary risk pricing of zombies. Non-zombies do not rely on the government's budget capacity in the same way and are not priced by the intermediary factor or either component of intermediary risk. The results are robust to using the capital ratio factor instead of the leverage factor to separate the two components, adding a market factor, and including the ten momentum portfolios.[5]

Zombies vs. Bank-Dependent Firms Zombies differ from bank-dependent firms in their government dependence. Like zombies, bank-dependent portfolios are priced by intermediary risk. Unlike zombies, the component of intermediary risk that is orthogonal to government risk drives the pricing result.

I identify bank-dependent firms using three measures: external-finance dependence, bank beta, and long-term debt issuance. First, I construct a measure for external-finance dependence in the spirit of Rajan and Zingales (1998), which represents the amount of a firm's desired investment that it cannot finance through internal cash flows alone. I use Datastream/Worldscope data on capex and cash flows from operations to construct firms' external-finance dependence, which is the ratio of capital expenditures less cash flows from operations to capex. To calculate the time-series of external-finance dependence for each firm, I calculate the external-finance ratio using data as available in the previous ten years. Second, I measure bank betas using each firm's bank beta using 24 to 60 months of monthly returns, as available, in the five years before July of year t, like the Fama–French pre-ranking betas. Third, Kashyap et al. (1994) define bank-dependent firms as

[5]See Table 1.11, Table 1.12, and Table 1.13.

companies that do not have a long-term issuer rating from S&P since these firms do not have easy access to capital markets. In Japan, I use an indicator for whether the firm has a long-term credit rating from Japan Credit Rating Agency, Ltd. This measure is an ex-post indicator for firms with credit ratings.

I classify bank-dependent firms as those in the top 50^{th} percentile using the three bank dependence measures. I form bank-dependent portfolios annually in June t for July t to June $t+1$, using accounting data available in December $t-1$. Zombie-ness and bank dependence are related; each of the three bank dependence measures has a significant correlation with the zombie indicator ranging from 9% to 12%, and zombies are more bank dependent than non-zombies using each measure.

I form quarterly portfolios of bank-dependent firms, separately for each measure of bank dependence, and I price the portfolios using the intermediary factor and its components. I use the two components of $LevFac_{JP}$ to price portfolios following the two-step procedure in Equations 2.9 and 2.10 and $\mathbf{f} = LevFac_{predicted}$ and $\mathbf{f} = LevFac_{residual}$, separately, to calculate the prices of risk.

Table 1.9 and Figure 1.10 show the cross-sectional pricing results. Bank-dependent portfolios are priced by the intermediary factor and the intermediary component orthogonal to government risk, $LevFac_{residual}$. Bank-dependent portfolios are not priced by the component correlated with government risk, $LevFac_{predicted}$. The results are similar using the capital ratio factor in place of the leverage factor and adding a market factor.[6] The intermediary factors price zombie portfolios and bank-dependent portfolios but do not price Japanese Fama–French portfolios since they do not sort in a way that gives heterogeneous exposure to intermediary beta. Sorting on bank dependence first gives portfolios an economically meaningful spread in intermediary beta.

1.4.2 Japanese Event Studies

I have previously shown that firms with direct dependence on the government respond to events when the government grows riskier. I now show the equivalent for companies with government dependence through the intermediary sector: when the intermediary sector grows riskier, returns for these indirectly-government-dependent companies fall. I show that Japanese zombies have higher beta to government risk than non-zombies. Zombies also have lower cumulative abnormal returns than non-zombies after a shock to the banking system. The results are like the U.S. event study results and reflect zombies' government dependence through the intermediary sector.

Table 1.10 shows the regression of daily returns on the government risk factor in Japan. Like the U.S. result, government-dependent firms have a higher beta to government risk. Zombies have a 30% larger beta

[6] See Table 1.14, Table 1.15, and Table 1.16.

than non-zombies. Unlike the U.S. government-dependent firms, zombies' government dependence is indirect. Zombies exist because banks forbear on their non-performing loans, and they rely on the government to continue allowing banks to do so. Consistent with the indirect mechanism, zombies have a higher beta to government risk than non-zombies, but the effect disappears when I control for bank returns.

Ross (2020) shows that zombies also have substantial negative abnormal returns around salient financial events. November 1997 marked the beginning of the "acute phase" of Japan's lost two decades and a period associated with tighter credit (Hoshi and Kashyap, 2010). During the month, four financial institutions unexpectedly failed, and Ross (2020) shows that cumulative abnormal returns of zombies were much lower than the cumulative abnormal returns of non-zombies.

1.5 Conclusion

Government-dependent companies are exposed to government risk. The dependence can be direct—like U.S. government suppliers, large banks, and auto companies—or through the intermediary sector, like Japanese zombies. In both cases, government-dependent firms' returns covary with the government's budget constraints, and firms with greater government risk exposure have higher expected returns.

1.6 Tables

Prices of Risk: $\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f$										
Portfolios	Gov't Suppliers + Banks + Autos			Gov't Suppliers			Fama–French			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.244	−0.127	−0.044	0.121	−0.553	−0.337	0.787	0.969	0.801	1.681
	(0.57)	(−0.18)	(−0.07)	(0.18)	(−0.54)	(−0.32)	(1.93)	(2.11)	(1.83)	(3.83)
GovFac	0.412	0.394	0.429	0.548	0.517	0.474	−0.052	−0.052	−0.009	
	(2.60)	(2.42)	(2.35)	(2.29)	(2.20)	(1.93)	(−0.34)	(−0.34)	(−0.08)	
$Mkt - R_f$		0.725	0.631		1.224	1.253		−0.197	−0.027	−0.952
		(1.07)	(0.85)		(1.32)	(1.18)		(−0.36)	(−0.05)	(−2.12)
SMB			−0.056			−0.271			−0.011	0.111
			(−0.21)			(−0.72)			(−0.06)	(1.03)
HML			0.329			1.069			−0.120	0.367
			(0.89)			(1.12)			(−0.65)	(3.38)
Ann. Risk Premium ($\sigma^\beta \times \lambda_{GovFac}$)	3.65	3.45	4.78	4.83	4.47	3.92	−0.21	−0.22	−0.02	
TS GRS p-value	0.00	0.00	0.00	0.42	0.46	0.50	0.00	0.00	0.00	0.00
MAPE (%)	0.76	0.58	0.56	0.73	0.59	0.55	0.57	0.16	0.13	0.12
TS Avg R^2	0.01	0.41	0.51	0.01	0.43	0.50	0.01	0.82	0.93	0.91
Months (T)	152	152	152	131	131	131	187	187	187	1,118
Portfolios (N)	31	31	31	25	25	25	25	25	25	25
80% Restriction	Yes	Yes	Yes	No	No	No	No	No	No	No

Table 1.1: Cross-Sectional Asset Pricing of U.S. Government-Dependent Portfolios. Table presents the cross-sectional pricing results for size-and-book-to-market monthly portfolios: 25 government suppliers portfolios, 6 bank portfolios, 6 auto portfolios, and 25 Fama–French portfolios. Government-dependent portfolios are required to have data for 80% of the time in the pooled regressions. The regressions test if the U.S. government-risk factor, *GovFac*, prices the portfolios. See the text for additional details on the factors and portfolios. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Ann. Risk Premium ($\sigma^\beta \times \lambda_{GovFac}$) is the annualized increase in expected risk premium associated with a one standard deviation increase in the portfolio's beta to the government risk factor. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2.

$\mathbb{E}[R^e_{i,t}] = \gamma_0 + \gamma_1(\text{Characteristic})$				
	(1)	(2)	(3)	(4)
Intercept	1.139	1.491	1.140	1.493
	(4.61)	(2.77)	(4.61)	(2.77)
$\mathbb{I}$(Government Supplier)	0.195	0.171		
	(2.26)	(2.04)		
Government Sales Ratio			0.239	0.207
			(2.15)	(1.88)
ln(Size)		0.001		0.001
		(0.02)		(0.02)
ln(B/M)		0.633		0.634
		(7.55)		(7.54)
Months (T)	462	462	462	462
Firms (N)	17,329	17,329	17,329	17,329

Table 1.2: Cross-Sectional Asset Pricing of U.S. Firms using Firm Characteristics. Table presents the cross-sectional pricing results for monthly firm returns. The regressions test if the government suppliers have higher expected returns, and if firms with greater government dependence have higher expected returns. Coefficients are the price of risk estimates, and Fama–MacBeth t-statistics are reported.

	(1)	(2)	(3)	(4)
	GovFac	*GovFac*	*GovFac*	*GovFac*
$Mkt - R_f$	0.014	0.011		
	(1.61)	(1.50)		
SMB	−0.022		−0.011	
	(−1.38)		(−0.73)	
HML	0.014			0.017
	(0.89)			(1.11)
Constant	0.195***	0.194***	0.203***	0.204***
	(5.27)	(5.33)	(5.74)	(5.75)
N	187	187	187	187
Adj. R^2	0.01	0.00	-0.00	0.00

Table 1.3: Spanning Tests of the U.S. Government Risk Factor. Table presents time-series regressions at the monthly level. The dependent variable is the U.S. government risk factor, *GovFac*. See the text for additional details on *GovFac*. Independent variables are Fama–French factors: the excess market return, *SMB*, and *HML*. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Examples of Government Suppliers	Examples of Non-suppliers
Aetna	Amazon
Anthem	Apple
Appian	AT&T
Boeing	Cisco
Booz Allen Hamilton	Coca-Cola
Caterpillar	Comcast
Con Edison	Disney
Corrections Corporation of America	Exxon Mobil
GE	Home Depot
Goodyear	Intel
HP	Johnson & Johnson
Honeywell	Mastercard
Huntington Ingalls	Merck
Lockheed Martin	Microsoft
Mathematica	Oracle
Northrop Grumman	Pepsi
PG&E	Pfizer
Raytheon	Proctor & Gamble
Texas Instruments	Verizon
Walgreens	Walmart

Table 1.4: Examples of Government Suppliers and Non-suppliers. Table presents examples of government suppliers and non-suppliers. Government suppliers are firms with more than 10% of their annual sales coming from the federal government, and each company listed as a government supplier has more than a year of government sales over 10%.

	(1) Gov't Suppliers − Non-suppliers	(2) Government Suppliers	(3) Non-suppliers	(4) Gov't Suppliers − Non-suppliers	(5) Government Suppliers	(6) Non-suppliers
GovFac	0.316**	0.327**	0.011**	0.392**	0.406**	0.014**
	(2.97)	(2.98)	(3.11)	(3.14)	(3.15)	(3.22)
Constant	0.000*	0.000*	0.000	0.001	0.001	0.000
	(2.15)	(2.12)	(1.21)	(1.81)	(1.79)	(0.69)
N	3,862	3,862	3,862	3,862	3,862	3,862
Adj. R^2	0.00	0.00	0.00	0.00	0.00	0.00
Year FE	No	No	No	Yes	Yes	Yes

Table 1.5: Beta of Government Suppliers to the U.S. Government Risk Factor. Table presents time-series regressions at the daily level. The dependent variable is the value-weighted portfolio return in percent. The government suppliers portfolio consists of firms with more than 10% of their annual sales coming from the federal government. The non-suppliers portfolio includes firms with than 10% of their annual sales coming from the federal government or no government sales reported. The independent variable is the U.S. government risk factor, *GovFac*. See the text for additional details on the *GovFac*. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Sample	All Commercial Banks					Top 50 Commercial Banks				
	(1) Return	(2) Return	(3) Return	(4) Return	(5) Return	(6) Return	(7) Return	(8) Return	(9) Return	(10) Return
$GovFac_{synthetic}$	0.007***	0.006***	0.008***	0.017***	0.018***	0.012***	0.008*	0.009*	0.016***	0.017***
	(4.52)	(3.67)	(4.88)	(9.97)	(10.41)	(3.98)	(2.28)	(2.56)	(4.51)	(4.73)
$GovFac_{synthetic} \times \mathbb{I}$(WSJ)		0.022***	0.021***	0.007	0.007		0.020**	0.019**	0.007	0.007
		(3.74)	(3.53)	(1.04)	(0.99)		(2.97)	(2.93)	(0.94)	(0.92)
$GovFac_{synthetic} \times \mathbb{I}$(Post)				−0.024***	−0.021***				−0.028**	−0.028**
				(−6.53)	(−5.80)				(−2.97)	(−2.88)
$GovFac_{synthetic} \times \mathbb{I}$(WSJ) $\times \mathbb{I}$(Post)				0.041***	0.040**				0.047**	0.047**
				(3.36)	(3.26)				(3.10)	(3.10)
Constant	0.072***	0.072***	−0.033	0.073***	−0.033	0.051***	0.051***	−0.045	0.051***	−0.045
	(46.70)	(46.72)	(−0.24)	(46.91)	(−0.25)	(16.54)	(16.55)	(−0.38)	(16.56)	(−0.38)
N	3,935,268	3,935,268	3,935,268	3,935,268	3,935,268	598,452	598,452	598,452	598,452	598,452
Adj. R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Year FE	No	No	Yes	No	Yes	No	No	Yes	No	Yes
SIC FE	No	No	Yes	No	Yes	No	No	Yes	No	Yes

Table 1.6: Beta of U.S. Commercial Banks to the Synthetic U.S. Government Risk Factor. Table presents time-series regressions run at the daily level. The dependent variable is firm i's return in percent. Independent variables are the synthetic U.S. government risk factor, $GovFac_{synthetic}$, and the factor interacted with indicator variables. See the text for additional details on $GovFac_{synthetic}$. $\mathbb{I}(\text{WSJ}) = 1$ if the bank is one of the 11 banks cited as too big to fail by *The WSJ*, and 0 otherwise. $\mathbb{I}(\text{Post}) = 1$ if the date is after September 20, 1984, and 0 otherwise. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Treatment Group	Big Three					Autos				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Return	Return	Return	Return	Return	Return	Return	Return	Return	Return
GovFac	0.686***	0.686***	0.869***	0.126***	0.135***	0.686***	0.685***	0.868***	0.125***	0.135***
	(66.33)	(66.28)	(72.39)	(7.10)	(4.63)	(66.33)	(66.09)	(72.22)	(7.07)	(4.62)
GovFac $\times$ $\mathbb{I}$(Treated)		0.655*	0.645*	−0.074	−0.158		0.499**	0.507**	0.145	0.060
		(2.08)	(2.00)	(−0.16)	(−0.33)		(3.13)	(2.93)	(0.66)	(0.21)
GovFac $\times$ $\mathbb{I}$(Post)				0.926***	0.946***				0.925***	0.944***
				(41.57)	(29.60)				(41.47)	(29.53)
GovFac $\times$ $\mathbb{I}$(Treated) $\times$ $\mathbb{I}$(Post)				1.521*	1.613*				0.647*	0.735
				(2.36)	(2.45)				(2.03)	(1.94)
Constant	0.036***	0.036***	0.054**	0.050***	0.109***	0.036***	0.036***	0.054**	0.050***	0.109***
	(39.55)	(39.55)	(2.68)	(48.17)	(5.44)	(39.55)	(39.55)	(2.68)	(48.17)	(5.44)
N	20,042,168	20,042,168	20,042,168	20,042,168	20,042,168	20,042,168	20,042,168	20,042,168	20,042,168	20,042,168
Adj. R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Year FE	No	No	Yes	No	Yes	No	No	Yes	No	Yes
SIC FE	No	No	Yes	No	Yes	No	No	Yes	No	Yes

Table 1.7: Beta of U.S. Auto Companies to the U.S. Government Risk Factor. Table presents time-series regressions at the daily level. The dependent variable is return in percent. Independent variables are the U.S. government risk factor, *GovFac*, and the factor interacted with indicator variables. See the text for additional details on *GovFac*. In columns 1 to 5, $\mathbb{I}(\text{Treated}) = 1$ if the firm is one of the Big Three automakers, and 0 otherwise. In columns 6 to 10, $\mathbb{I}(\text{Treated}) = 1$ if the firm is an automaker, and 0 otherwise. $\mathbb{I}(\text{Post}) = 1$ if the date is after December 19, 2008, and 0 otherwise. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Prices of Risk: $\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f$									
Portfolios	Zombies			Non-zombies			Fama–French		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$LevFac_{JP}$	11.790			−3.212			5.902		
	(2.19)			(−0.56)			(1.31)		
$LevFac_{predicted}$		1.365			0.630			1.340	
		(1.96)			(0.76)			(2.06)	
$LevFac_{residual}$			7.781			7.920			9.320
			(1.69)			(1.31)			(1.60)
Ann. Risk Premium ($\sigma^\beta \times \lambda$)	2.01	1.91	1.62	−0.82	1.47	1.80	1.19	2.14	1.42
TS GRS p-value	0.11	0.23	0.24	0.33	0.11	0.57	0.42	0.35	0.08
MAPE (%)	2.14	3.05	2.18	2.76	3.26	2.60	2.37	2.77	2.42
TS Avg R^2	0.14	0.02	0.18	0.13	0.03	0.12	0.15	0.01	0.18
Quarters (T)	79	65	65	58	50	50	82	65	65
Portfolios (N)	25	25	25	25	25	25	25	25	25

Table 1.8: Intermediary Asset Pricing of Japanese Portfolios. Table presents the cross-sectional pricing results for size-and-book-to-market quarterly portfolios: 25 zombie portfolios, 25 non-zombie portfolios, and 25 Fama–French portfolios. The regressions test if the Japanese intermediary factor and its components price the portfolios. $LevFac_{JP}$ is the Japanese intermediary leverage factor, and its components are $LevFac_{predicted}$ and $LevFac_{residual}$. $LevFac_{predicted}$ is correlated with government risk, and $LevFac_{residual}$ is orthogonal to government risk. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium ($\sigma^\beta \times \lambda$) is the annualized increase in expected risk premium associated with a one standard deviation increase in the portfolio's beta to the intermediary factor or factor component. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2. See Tables 1.11, 1.12, and 1.13 for results with the inclusion of the market factor, results using the capital ratio factor, results adding the 10 momentum portfolios, and results with a horserace between the two components of the intermediary factors.

Prices of Risk: $\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f$									
Bank Dependence Measure	External Finance			Bank Beta			Long-Term Issuer		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$LevFac_{JP}$	11.787			9.017			14.209		
	(2.43)			(2.16)			(2.83)		
$LevFac_{predicted}$		1.409			0.737			1.636	
		(1.62)			(1.21)			(1.83)	
$LevFac_{residual}$			10.529			11.376			14.320
			(2.22)			(2.42)			(2.76)
Ann. Risk Premium ($\sigma^\beta \times \lambda$)	3.02	2.03	2.49	2.32	1.45	2.98	3.08	2.76	3.32
TS GRS p-value	0.16	0.76	0.28	0.01	0.01	0.02	0.01	0.09	0.06
MAPE (%)	1.96	3.12	1.88	2.34	3.42	2.11	2.13	2.65	2.19
TS Avg R^2	0.20	0.03	0.22	0.19	0.03	0.24	0.11	0.02	0.13
Quarters (T)	68	65	65	79	65	65	75	63	63
Portfolios (N)	35	35	35	35	35	35	35	35	35

Table 1.9: Intermediary Asset Pricing of Japanese Bank-Dependent Portfolios. Table presents the cross-sectional pricing results for quarterly portfolios: 25 size-and-book-to-market bank-dependent portfolios and 10 momentum bank-dependent portfolios. Firms are classified as bank dependent using three bank dependence measures separately, and bank-dependent portfolios are formed of bank-dependent firms. See the text for additional details on the bank dependence measures and portfolio construction. The regressions test if the Japanese intermediary factor and its components price the portfolios. $LevFac_{JP}$ is the Japanese intermediary leverage factor, and its components are $LevFac_{predicted}$ and $LevFac_{residual}$. $LevFac_{predicted}$ is correlated with government risk, and $LevFac_{residual}$ is orthogonal to government risk. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium ($\sigma^\beta \times \lambda$) is the annualized increase in expected risk premium associated with a one standard deviation increase in the portfolio's beta to the intermediary factor or factor component. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2. See Tables 1.14, 1.15, and 1.16 for results with the inclusion of the market factor, results using the capital ratio factor, and results with a horserace between the two components of the intermediary factors.

	(1) Return	(2) Return	(3) Return	(4) Return	(5) Return
$GovFac_{JP}$	1.183***	0.985***	1.123***	0.387***	−0.010
	(87.12)	(40.47)	(44.31)	(18.33)	(−0.48)
$GovFac_{JP} \times \mathbb{I}$(Zombie)		0.294***	0.251***	0.042	0.007
		(10.16)	(8.53)	(1.72)	(0.31)
Bank Return				53.378***	6.588***
				(270.44)	(31.42)
Bank Return×$\mathbb{I}$(Zombie)				3.645***	2.280***
				(15.27)	(10.48)
$\mathbb{I}$(Zombie)					0.002
					(0.62)
Market Return					73.977***
					(376.07)
Constant	0.003*	0.003*	−0.063***	−0.007	0.006
	(1.96)	(2.35)	(−5.23)	(−0.61)	(0.51)
N	2,436,106	2,436,106	2,436,106	2,436,106	2,272,511
Adj. R^2	0.00	0.00	0.01	0.20	0.28
Year FE	No	No	Yes	Yes	Yes
SIC FE	No	No	Yes	Yes	Yes

Table 1.10: Beta of Japanese Firms to the Japanese Government Risk Factor. Table presents time-series regressions at the daily level. The dependent variable is the return in basis points. Independent variables include the Japanese government risk factor, $GovFac_{JP}$, and the Japanese value-weighted bank return. $\mathbb{I}$(Zombie) = 1 if the firm is a zombie, and 0 otherwise. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

1.7 Figures

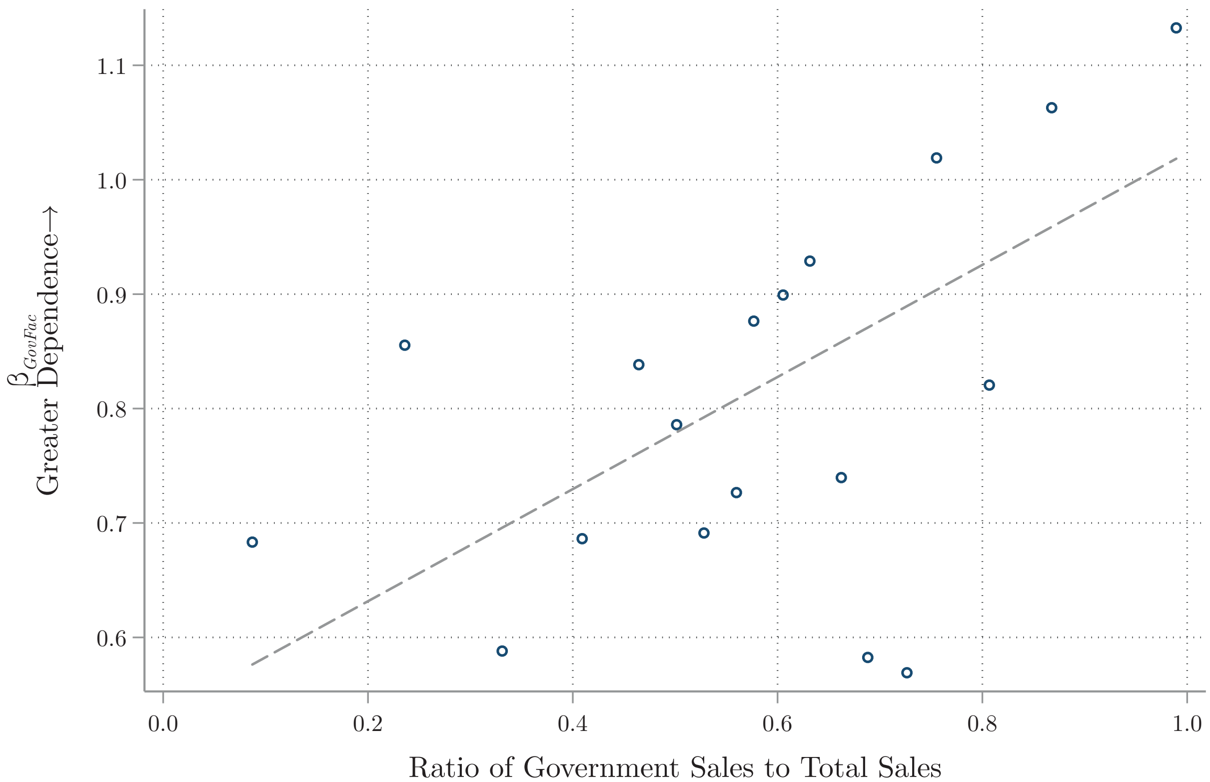


Figure 1.1: Government Risk and the Ratio of Government Sales To Total Sales. Figure is a binned scatterplot of beta to the U.S. government risk factor against the average government sales ratio. Each value is calculated at the industry level.

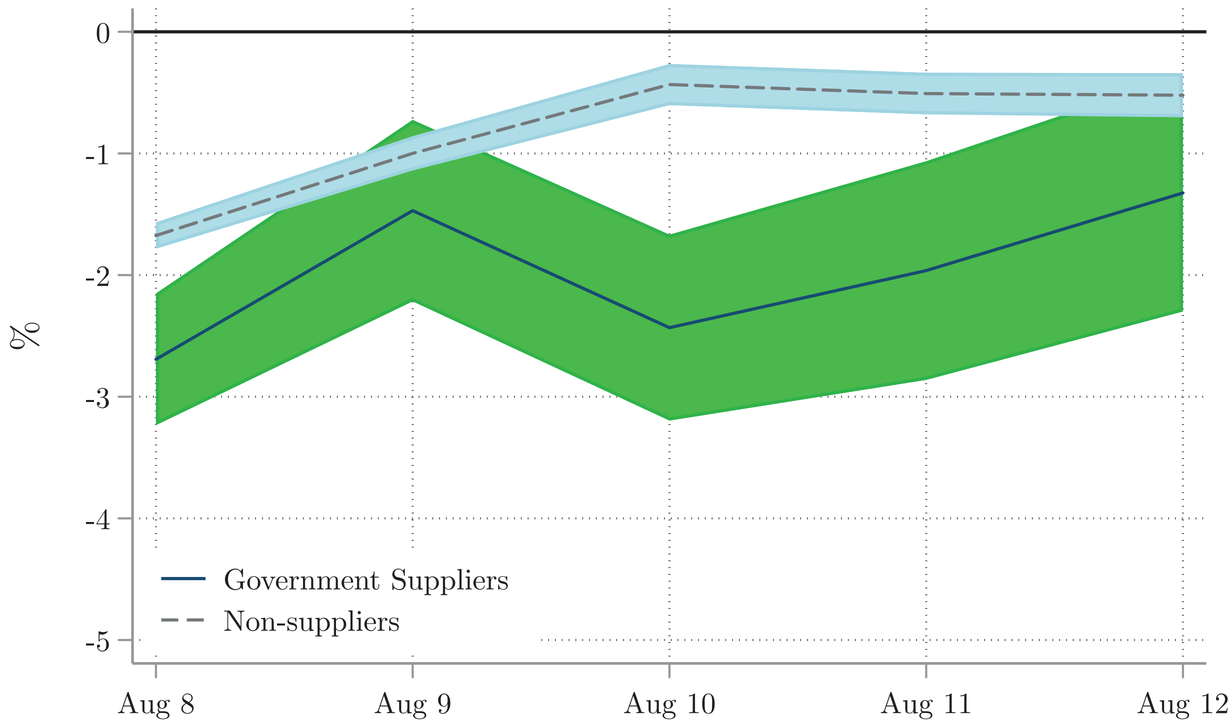


Figure 1.2: Cumulative Abnormal Return of Government Suppliers and Non-suppliers After the U.S. Sovereign Debt Downgrade. Figure shows the daily average cumulative abnormal returns in the week after the U.S. sovereign debt downgrade and its standard errors. I calculate each firm's abnormal returns as the difference between the realized return and predicted return using the estimated CAPM market beta before August 5, 2011, the day of the downgrade. I calculate the daily average separately for government suppliers and non-suppliers.

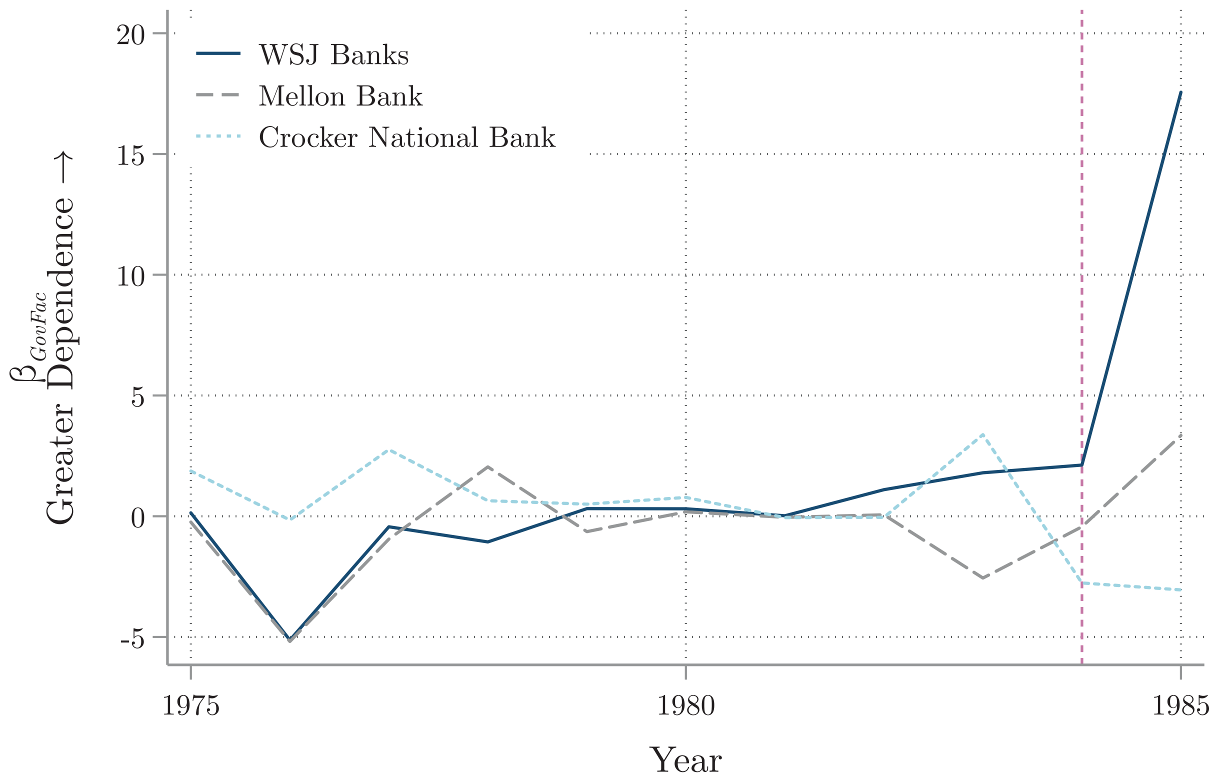


Figure 1.3: Beta to Synthetic U.S. Government Risk Factor. Figure shows the average beta to the synthetic U.S. government risk factor for the 11 largest banks cited by the *WSJ* and the beta for the next largest banks, Mellon Bank and Crocker National Bank. Betas are calculated monthly and averaged to the annual level. Vertical line marks 1984, the year of the too big to fail event.

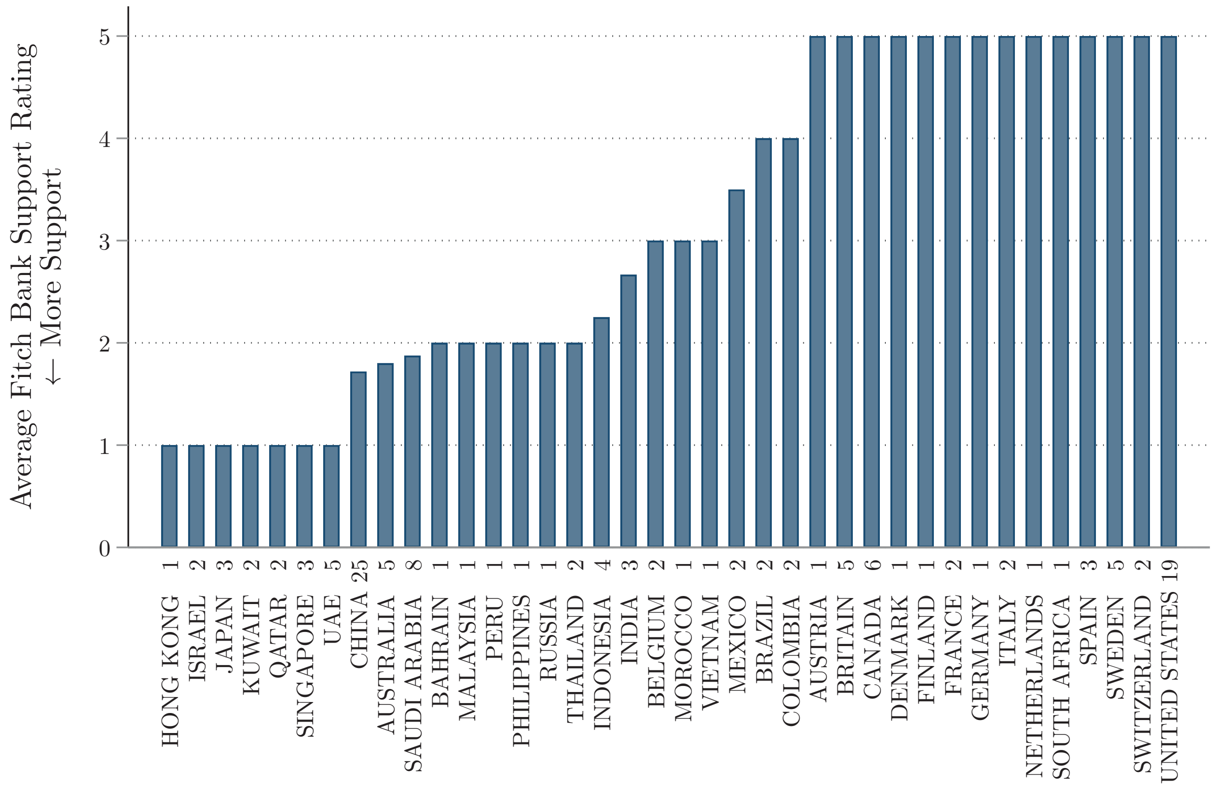


Figure 1.4: Average Fitch Bank Support Rating. Figure shows each country's average Fitch bank support rating, calculated as the average rating for banks included in the Bloomberg Banks Index. The number next to each country's label is the number of ratings available for that country.

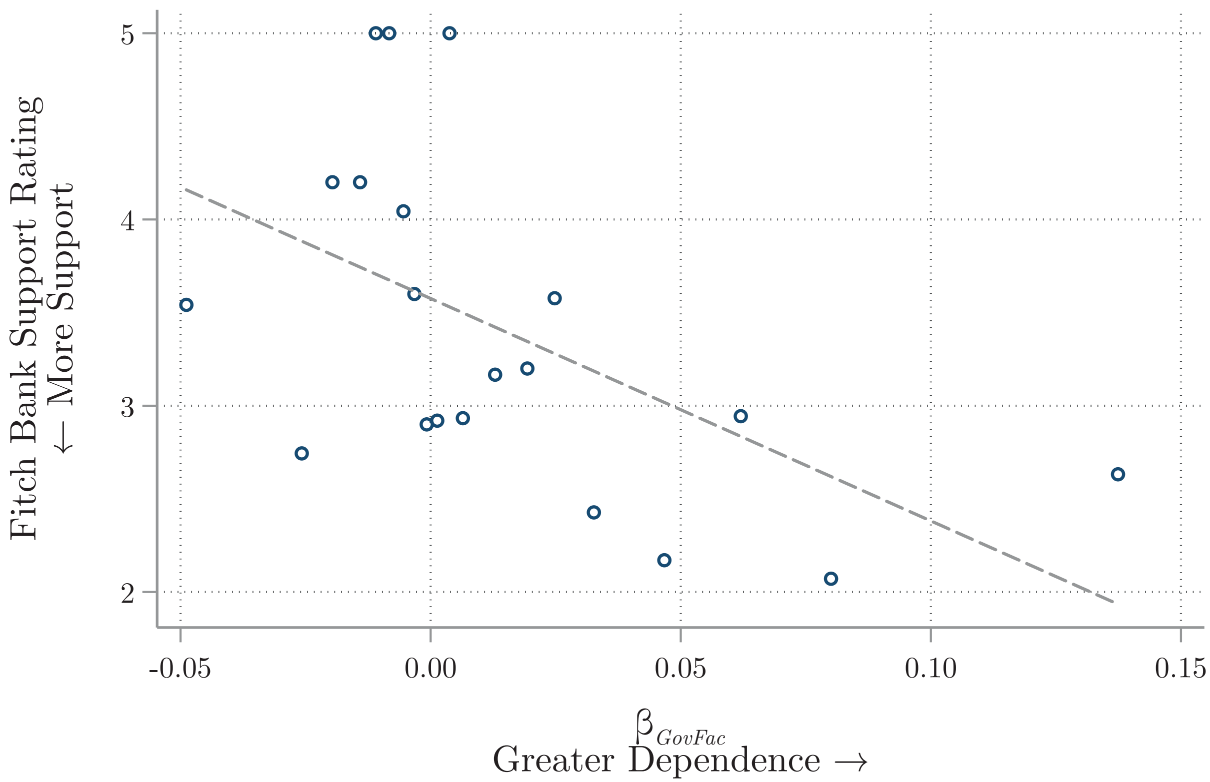


Figure 1.5: Fitch Bank Support Ratings and Beta to Government Risk. Figure is a binned scatterplot of countries' average Fitch bank support ratings against banks' return beta to the domestic government risk factor. I calculate a country-specific *GovFac* for each country in a method analogous to the benchmark U.S.-based *GovFac*. I exclude Saudi Arabia given its large outlier value.

Figure 1.6: Beta to U.S. Government Risk Factor. Figure shows the average beta to the U.S. government risk factor for the Big Three automakers and a control group of non-bank, non-autos. Betas are calculated monthly and averaged to the annual level. Vertical line marks 2008, the year of the Global Financial Crisis auto bailout.

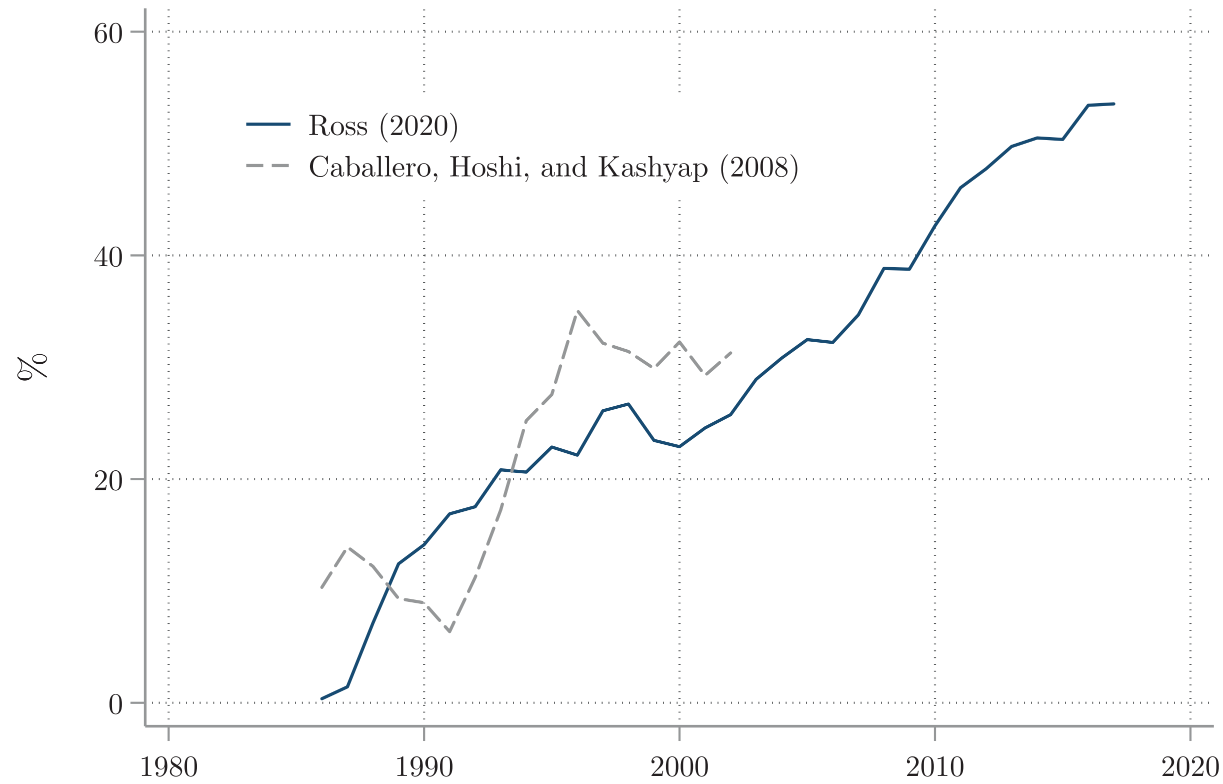


Figure 1.7: Percentage of Zombie Firms in Japan. Figure compares the percentage of Japanese zombies in the data and the zombie percentage from Caballero et al. (2008). Zombies are identified on a monthly basis, and the plotted percentage is the annual average.

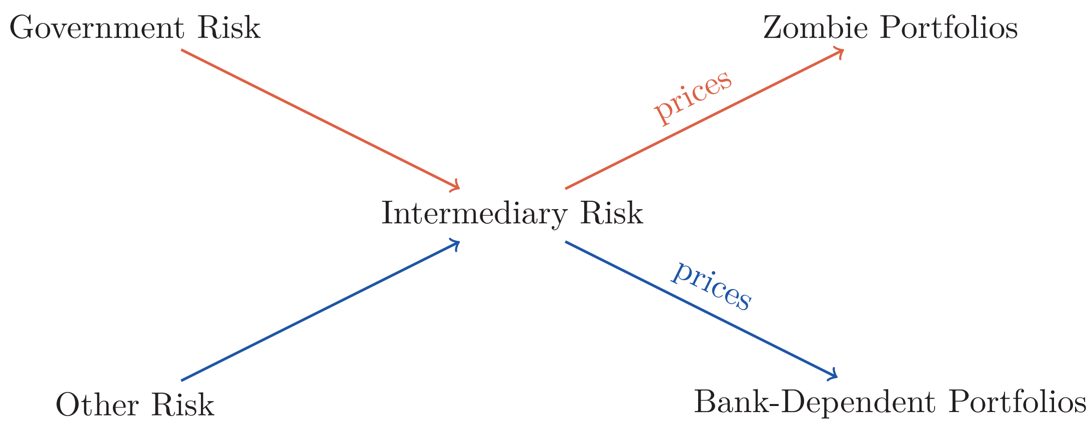


Figure 1.8: Intermediary Asset Pricing Summary. Figure summarizes the Japanese intermediary asset pricing results. Intermediary risk factors price zombie portfolios and bank-dependent portfolios, which differ in their government dependence. Under government-condoned forbearance, intermediary risk has two components: one correlated with government risk, one orthogonal to government risk. The former prices zombies, and the latter prices bank-dependent portfolios.

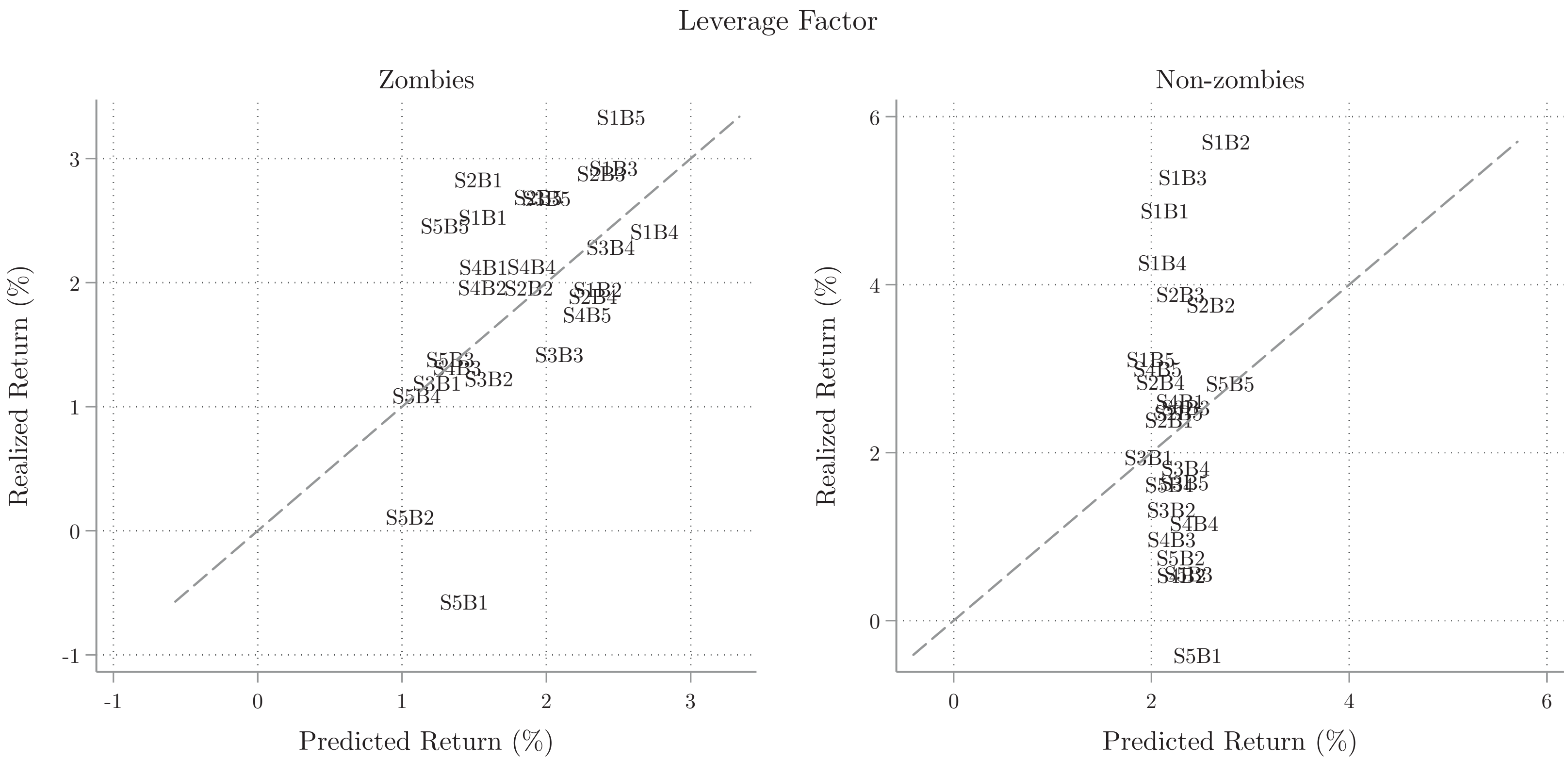


Figure 1.9: Realized vs. Predicted Returns using the Intermediary Leverage Factor. Figure shows the realized and predicted excess returns of size-and-book-to-market portfolios. 25 zombie portfolios and 25 non-zombie portfolios are used. Predicted returns are calculated using quarterly regressions and the intermediary leverage factor, $LevFac_{JP}$.

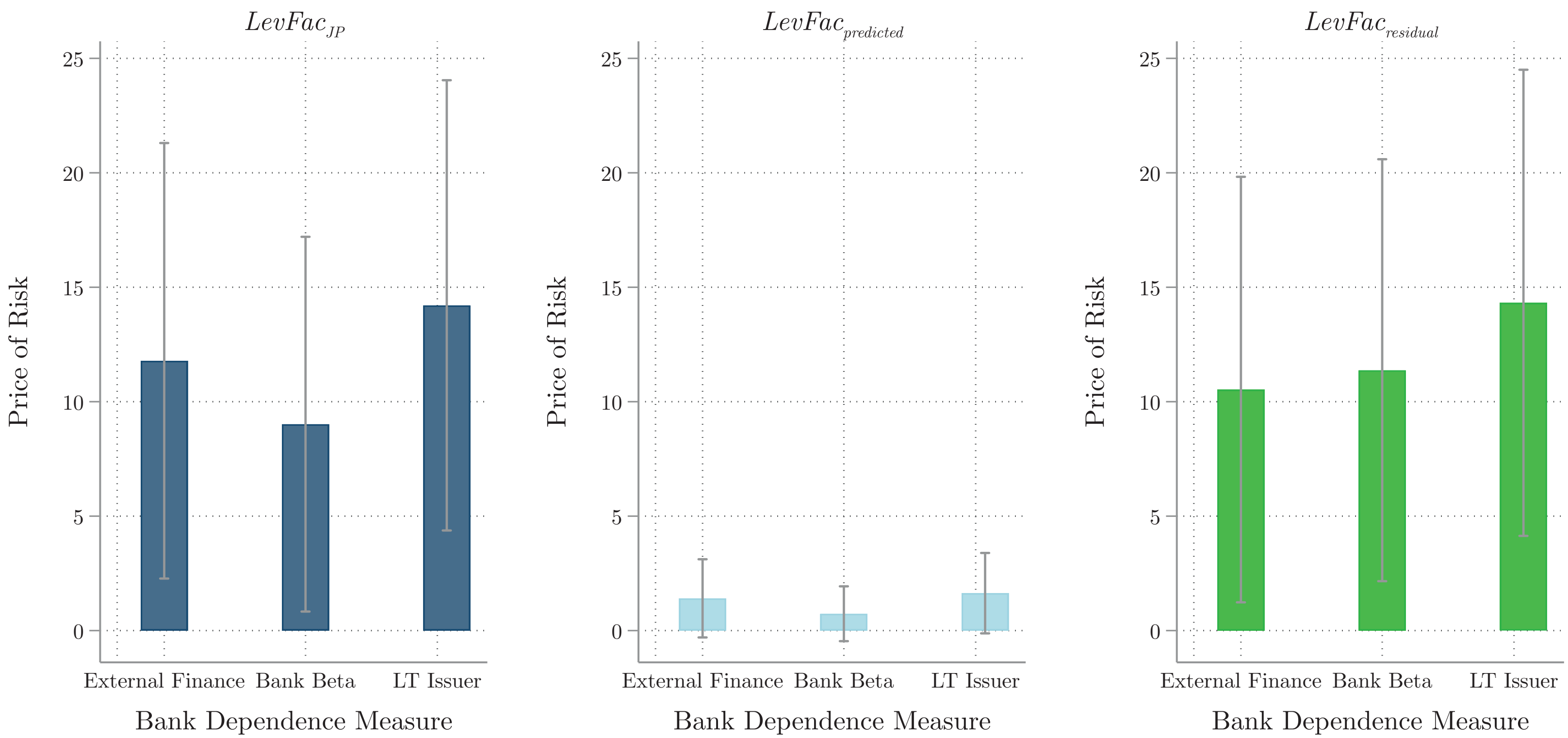


Figure 1.10: Price of Risk for Bank-Dependent Portfolios. Figure shows the price of risk from cross-sectional regressions of bank-dependent portfolio returns and GMM standard error bars. Each bar represents the price of risk calculated from the cross-sectional regression of 25 bank-dependent portfolios on the intermediary leverage factor or a component of the intermediary leverage factor. Three sets of 25 bank-dependent portfolios are used. Each set of portfolios is sorted on size and book-to-market, and firms are categorized as bank dependent using three separate measures of bank dependence: external finance, bank beta, and long-term issuer. $LevFac_{JP}$ is the intermediary leverage factor, and $LevFac_{predicted}$ and $LevFac_{residual}$ are its components. $LevFac_{predicted}$ is correlated with government risk, and $LevFac_{residual}$ is orthogonal to government risk. See the text for details on the construction of the factors and portfolios.

1.8 Appendix

1.8.1 Data

U.S. Government Risk Factor Correlations The U.S. government risk factor, *GovFac*, is correlated with other measures of government risk. I study two sets of measures. First, I show that *GovFac* is significantly correlated with the news-implied volatility indexes from Manela and Moreira (2017). Second, I show that *GovFac* correlates with the Risk 1A long-short portfolio returns from Ross (2019).

Manela and Moreira (2017) create a news-implied volatility index, *NVIX*, which is a text-based measure of uncertainty using articles from *The Wall Street Journal*. *NVIX* spikes during financial crises, market crashes, and periods of elevated policy uncertainty. *NVIX* is decomposed into categories of disaster risk, including "Financial Intermediation," "Stock Markets," and "Government," which reflects policy-related uncertainty. An increase in *NVIX* or its components reflects an increase in risk and uncertainty.

Ross (2019) uses textual analysis of Item 1A of firms' annual filings to create 50 long-short portfolios based on firms' exposure to each risk. A firm's exposure is captured by the firm's relevance to common risks in Item 1A. "Taxes" or "Regulations" risk portfolios are two of the government-related portfolios.

Table 1.17 regresses the U.S. government risk factor on the news-implied volatility indexes and the Risk 1A portfolios. When the government becomes more constrained (*GovFac* decreases), news-implied volatility increases both in the aggregate and in the Government, Financial Intermediation, and Stock Market components. When government risk increases, firms with high Tax or Regulations risk exposure also have lower returns.

Constructing Par-equivalent CDS U.S. sovereign CDS data are from Markit and begins in 2003. For the 1984 event study, I construct a longer time-series by creating a synthetic sovereign CDS spread that is the par-equivalent CDS spread and begins in 1962. Then I use the synthetic spread and the same method from Equations 1.3 and 1.4 to form the synthetic government risk factor, $GovFac_{synthetic}$.

To create the par-equivalent CDS spread, I use the CRSP Treasuries dataset, Libor swap rates, and the U.S. yield curve. For each date, I choose the bond in the CRSP Treasuries dataset that is deliverable against a 5-year CDS contract and cheapest to buy. I use this bond's dirty price and coupon. I iterate through CDS spread values between 0 and 250bps, incrementing by 0.25bps, to find the CDS spread that gives the CDS-implied bond price that most closely matches the realized bond price. I assume a recovery rate of 0.4, a semi-annual CDS, and a face value of 100. I use Libor swap rates, when available, for the risk-free rates, and I linearly interpolate these swap rates to get semi-annual rates. When Libor is unavailable, I use the U.S. Treasury yield curve from the St. Louis FRED.

Figure 1.11 plots the par-equivalent synthetic sovereign CDS spread, spliced with the actual U.S. sovereign CDS spread from Markit. The synthetic spread is demeaned and scaled to match the actual CDS spread on the first day the CDS spread data.

1.8.2 U.S. Event Studies Details

Banks In Section 1.3.2, I show that the 11 *WSJ* banks have higher beta to government risk than other commercial banks. In this section, I show that the result is robust to adding additional controls, using a shorter period, separate estimations for national and commercial banks, restricting the control group, and restricting the sample to banks on the border of the too big to fail cutoff. The result is also insignificant in a placebo test. Table 1.6 shows that after the *WSJ* event, the 11 *WSJ* banks have higher beta to government risk than other commercial banks. Table 1.18 shows the result is robust to adding controls for individual indicators, the market return, the bank's market capitalization, and the bank's assets at the end of the prior year.

Next, I run difference-in-difference regressions to further support that the 11 *WSJ* banks have higher beta to government risk than other commercial banks. First, I calculate each bank i's monthly beta to the synthetic government risk factor, $\beta_{GovFac_{synthetic,i,t}}$. Then, I regress this beta on indicators for being one of the 11 banks in the treatment group, after the *WSJ* article publication, and both. I control for each bank's monthly market beta, market capitalization, and assets.

$$\begin{aligned}\beta_{GovFac_{synthetic},i,t} = \alpha \\ &+ \gamma_1 \mathbb{I}(\text{Treated}) \\ &+ \gamma_2 \mathbb{I}(\text{Post}) \\ &+ \gamma_3 \mathbb{I}(\text{Treated}) \times \mathbb{I}(Post) \\ &+ \gamma_4 \beta_{Market,t} + \gamma_5 \text{Size}_{i,t} + \gamma_6 \text{Assets}_{i,t}.\end{aligned} \tag{1.13}$$

Table 1.19 shows the difference-in-difference regression of the beta to the synthetic U.S. government risk factor. After the *WSJ* article was published, the 11 cited banks have a higher beta to the government risk than other banks. Over an eight-year window of four years before the event and four years after the event, the results are stronger because there are many industry changes over the full period, including bank mergers in the 1980s and 1990s. The *WSJ* banks have a higher beta to government risk after the event, and the result holds for national and state commercial banks separately. Table 1.19 Panel B shows the result is robust to restricting the control group to only the largest 50 banks at each point in time. This result shows the 11 banks became more government dependent after the *WSJ* event even compared to other big banks.

I also run a placebo regression for robustness. I show there is no effect using a placebo event date of 1 year before the event or using a placebo treatment group of the intended national banks. I change the time indicator as one year before the *WSJ* event. In this regression, the difference-in-difference coefficient should be zero. Table 1.20 shows that the difference-in-difference coefficient is not significant for national and state commercial banks, particularly over the window of four years earlier and four years following the placebo event. This result shows the importance of the timing of the *WSJ* event.

Before the event, it was unclear where the cutoff fell between too big to fail banks and too small to save banks. Since the event occurred during the Continental Illinois bailout, Continental Illinois itself proved too big to fail, but the cutoff was unknown. I compare the beta of large banks near the too big to fail policy cutoff by restricting the sample to banks that were larger than Continental Illinois and in the top 25 banks in 1984. Table 1.21 shows the divergence in government dependence between the banks that were larger than Continential Illinois but covered by the policy and the banks that were slightly smaller.

Autos Table 1.7 shows that auto companies' returns have higher beta to government risk than other companies after the announcement of government support for the auto industry in the Global Financial Crisis. Table 1.22 shows this is robust to adding additional controls, including the market return and industry fixed effects.

1.8.3 Intermediary Asset Pricing Details

Leverage and Capital Ratio Factors in the U.S. and Japan Leverage and the capital ratio are reciprocals, and the two intermediary factors should have opposite signs if the factors are constructed from similar firms. In the U.S., both the leverage and capital ratio factors have a positive and significant price of risk (Adrian et al. (2014) and He et al. (2017)) because they are formed from datasets that use different firms as intermediaries. The leverage factor uses data on securities broker-dealers from the Flow of Funds, which captures only the U.S. subsidiary component. The capital ratio factor uses data on primary dealer counterparties of the NY Fed, matched to the publicly-traded holding company level, and this list includes foreign dealers.

In Japan, securities broker-dealers and primary dealers overlap more than in the U.S. The Japanese intermediary factors have a -51% correlation, which is significant at the $\alpha = 0.01$ level. In the U.S., the factors have a correlation of -4.9% over the same period.[7]

[7] Using updated data of the U.S. factors from Tyler Muir's and Asaf Manela's websites, the U.S. factors have a correlation of 0.90% from 1970Q1 to 2017Q3. Using data available from 1998Q1, the start of the Japanese leverage factor data availability, the U.S. factors have a correlation of -4.9%. He et al. (2017) find that in the U.S., the two factors have a 14% correlation between 1970Q1 and 2012Q4.

1.8.4 Appendix Tables

Prices of Risk: $\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f$

Panel A: Leverage Factor

	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$LevFac_{JP}$	11.790	13.020	−3.212	−4.030	5.902	8.327	8.077	8.357	−3.010	−2.760
	(2.19)	(2.38)	(−0.56)	(−0.65)	(1.31)	(1.41)	(1.68)	(1.77)	(−0.59)	(−0.54)
$Mkt - R_f$		−1.576		3.741		−0.108		−1.240		2.838
		(−0.77)		(1.19)		(−0.06)		(−0.64)		(1.12)
Ann. Risk Premium ($\sigma^\beta \times \lambda$)	2.01	2.32	−0.82	−1.39	1.19	1.65	1.51	1.70	−0.75	−0.88
TS GRS p-value	0.11	0.07	0.33	0.34	0.42	0.46	0.14	0.06	0.59	0.60
MAPE (%)	2.14	0.88	2.76	1.43	2.37	0.87	1.95	0.77	2.48	1.28
TS Avg R^2	0.14	0.70	0.13	0.58	0.15	0.73	0.16	0.69	0.15	0.59
Quarters (T)	79	79	58	58	82	82	79	79	58	58
Portfolios (N)	25	25	25	25	25	25	35	35	35	35

Panel B: Capital Ratio Factor

	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$CapFac_{JP}$	−8.675	−9.601	−2.644	−3.910	−4.585	−4.378	−6.531	−6.930	−2.728	−3.744
	(−1.97)	(−1.91)	(−0.70)	(−0.99)	(−0.91)	(−0.84)	(−1.71)	(−1.69)	(−0.72)	(−0.93)
$Mkt - R_f$		−1.531		−2.694		0.056		−1.442		−2.747
		(−0.87)		(−1.06)		(0.02)		(−0.93)		(−1.18)
Ann. Risk Premium ($\sigma^\beta \times \lambda$)	−1.97	−2.31	−1.41	−2.76	−0.93	−1.07	−1.61	−1.74	−1.39	−2.44
TS GRS p-value	0.20	0.43	0.83	0.93	0.42	0.68	0.37	0.55	0.43	0.56
MAPE (%)	2.73	0.82	2.77	1.12	2.59	0.46	2.54	0.78	2.62	0.98
TS Avg R^2	0.18	0.71	0.15	0.53	0.17	0.77	0.18	0.70	0.16	0.55
Quarters (T)	55	55	42	42	55	55	55	55	42	42
Portfolios (N)	25	25	25	25	25	25	35	35	35	35

Table 1.11: Intermediary Asset Pricing of Japanese Portfolios. Table presents the cross-sectional pricing results for 25 size-and-book-to-market and 10 momentum quarterly portfolios. 35 zombie portfolios, 35 non-zombie portfolios, and 25 Fama–French portfolios are used. The regressions test if a Japanese intermediary factor prices the portfolios. $LevFac_{JP}$ is the Japanese intermediary leverage factor, and $CapFac_{JP}$ is the Japanese intermediary capital ratio factor. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium ($\sigma^\beta \times \lambda$) is the annualized increase in expected risk premium associated with a one standard deviation increase in the beta to the intermediary factor. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2.

Prices of Risk: $\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f$

Panel A: $LevFac_{predicted}$

	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$LevFac_{predicted}$	1.365	1.372	0.630	0.589	1.340	1.323	1.493	1.506	0.834	0.820
	(1.96)	(2.02)	(0.76)	(0.79)	(2.06)	(1.95)	(1.99)	(2.14)	(1.05)	(1.06)
$Mkt - R_f$		−0.780		0.064		−0.670		−0.823		−0.284
		(−0.46)		(0.03)		(−0.30)		(−0.47)		(−0.13)
Ann. Risk Premium	1.91	1.83	1.47	1.47	2.14	2.30	2.09	1.98	1.90	1.96
TS GRS p-value	0.23	0.33	0.11	0.12	0.35	0.53	0.50	0.62	0.58	0.65
MAPE (%)	3.05	0.74	3.26	1.37	2.77	0.57	3.03	0.68	3.22	1.15
TS Avg R^2	0.02	0.70	0.03	0.55	0.01	0.79	0.02	0.71	0.03	0.57
Quarters (T)	65	65	50	50	65	65	65	65	50	50
Portfolios (N)	25	25	25	25	25	25	35	35	35	35

Panel B: $LevFac_{residual}$

	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$LevFac_{residual}$	7.781	8.909	7.920	6.879	9.320	9.906	7.068	7.692	7.278	6.924
	(1.69)	(1.78)	(1.31)	(1.24)	(1.60)	(1.50)	(1.69)	(1.79)	(1.25)	(1.32)
$Mkt - R_f$		−0.749		0.757		0.113		−0.943		0.225
		(−0.49)		(0.25)		(0.05)		(−0.60)		(0.10)
Ann. Risk Premium	1.62	1.84	1.80	2.00	1.42	1.98	1.56	1.67	1.63	1.93
TS GRS p-value	0.24	0.24	0.57	0.61	0.08	0.13	0.33	0.30	0.82	0.88
MAPE (%)	2.18	0.87	2.60	1.21	2.42	0.84	1.96	0.77	2.37	1.00
TS Avg R^2	0.18	0.71	0.12	0.55	0.18	0.79	0.19	0.71	0.13	0.57
Quarters (T)	65	65	50	50	65	65	65	65	50	50
Portfolios (N)	25	25	25	25	25	25	35	35	35	35

Panel C: $LevFac_{predicted}$ and $LevFac_{residual}$

	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$LevFac_{predicted}$	1.070	0.914	0.401	−0.039	1.242	0.861	1.396	1.337	0.658	0.450
	(1.64)	(1.34)	(0.54)	(−0.06)	(1.76)	(1.05)	(2.10)	(1.90)	(1.01)	(0.80)
$LevFac_{residual}$	2.909	4.141	6.421	6.576	1.743	3.922	0.871	1.317	4.672	4.899
	(0.53)	(0.69)	(1.09)	(1.10)	(0.29)	(0.69)	(0.16)	(0.22)	(0.87)	(0.95)
$Mkt - R_f$		−0.629		0.624		−0.528		−0.743		−0.138
		(−0.39)		(0.23)		(−0.24)		(−0.43)		(−0.07)
TS GRS p-value	0.19	0.38	0.12	0.18	0.35	0.62	0.43	0.65	0.62	0.75
MAPE (%)	3.05	0.72	3.39	1.30	2.77	0.67	3.03	0.69	3.36	1.09
TS Avg R^2	0.20	0.72	0.15	0.57	0.19	0.81	0.22	0.72	0.16	0.59
Quarters (T)	65	65	50	50	65	65	65	65	50	50
Portfolios (N)	25	25	25	25	25	25	35	35	35	35

Table 1.12: Intermediary Asset Pricing with Components of $LevFac_{JP}$. Table presents the cross-sectional pricing results for 25 size-and-book-to-market and 10 momentum quarterly portfolios. 35 zombie portfolios, 35 non-zombie portfolios, and 25 Fama–French portfolios are used. The regressions test if the components of $LevFac_{JP}$, the Japanese intermediary leverage factor, price the portfolios. $LevFac_{predicted}$ is the component correlated with government risk, and $LevFac_{residual}$ is the component orthogonal to government risk. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium is the annualized increase in expected risk premium associated with a one standard deviation increase in the beta to the intermediary factor component: $\sigma^\beta \times \lambda$. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2.

Prices of Risk: $\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f$										
Panel A: *CapFac*$_{predicted}$										
	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$CapFac_{predicted}$	−2.735	−2.749	−1.262	−1.180	−2.684	−2.649	−2.990	−3.018	−1.671	−1.643
	(−1.96)	(−2.02)	(−0.76)	(−0.79)	(−2.06)	(−1.95)	(−1.99)	(−2.14)	(−1.05)	(−1.06)
$Mkt - R_f$		−0.780		0.064		−0.670		−0.823		−0.284
		(−0.46)		(0.03)		(−0.30)		(−0.47)		(−0.13)
Ann. Risk Premium	−1.88	−1.81	−1.45	−1.45	−2.11	−2.26	−2.05	−1.95	−1.88	−1.93
TS GRS p-value	0.23	0.31	0.18	0.19	0.26	0.41	0.48	0.57	0.68	0.74
MAPE (%)	2.83	0.73	2.97	1.32	2.68	0.51	2.76	0.67	2.88	1.08
TS Avg R^2	0.02	0.70	0.03	0.55	0.01	0.79	0.02	0.71	0.03	0.57
Quarters (T)	65	65	50	50	65	65	65	65	50	50
Portfolios (N)	25	25	25	25	25	25	35	35	35	35
Panel B: *CapFac*$_{residual}$										
	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$CapFac_{residual}$	−7.487	−9.234	−3.520	−2.616	−5.221	−11.030	−6.121	−7.455	−2.942	−2.466
	(−1.99)	(−1.85)	(−0.87)	(−0.74)	(−1.00)	(−1.11)	(−1.87)	(−1.76)	(−0.78)	(−0.74)
$Mkt - R_f$		−1.000		0.124		0.414		−0.962		−0.149
		(−0.59)		(0.05)		(0.15)		(−0.63)		(−0.07)
Ann. Risk Premium	−1.88	−2.13	−1.38	−1.47	−0.87	−1.77	−1.61	−1.68	−1.18	−1.35
TS GRS p-value	0.23	0.22	0.61	0.70	0.09	0.15	0.33	0.32	0.77	0.86
MAPE (%)	2.18	0.89	2.55	1.24	2.42	0.89	1.96	0.78	2.32	1.02
TS Avg R^2	0.15	0.70	0.13	0.55	0.15	0.78	0.15	0.71	0.14	0.57
Quarters (T)	65	65	50	50	65	65	65	65	50	50
Portfolios (N)	25	25	25	25	25	25	35	35	35	35
Panel C: *CapFac*$_{predicted}$ and *CapFac*$_{residual}$										
	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$CapFac_{predicted}$	−1.839	−1.752	−0.857	−0.615	−2.696	−2.403	−2.436	−2.330	−1.495	−1.406
	(−1.51)	(−1.38)	(−0.59)	(−0.51)	(−1.84)	(−1.54)	(−1.97)	(−1.85)	(−1.13)	(−1.10)
$CapFac_{residual}$	−5.026	−6.788	−2.139	−1.754	0.138	−1.052	−2.664	−4.110	−1.013	−0.805
	(−1.44)	(−1.49)	(−0.63)	(−0.51)	(0.02)	(−0.17)	(−0.79)	(−0.98)	(−0.29)	(−0.25)
$Mkt - R_f$		−0.643		−0.153		−0.608		−0.511		−0.403
		(−0.40)		(−0.06)		(−0.28)		(−0.32)		(−0.19)
TS GRS p-value	0.24	0.39	0.10	0.17	0.24	0.45	0.43	0.61	0.41	0.57
MAPE (%)	2.83	0.68	3.14	1.29	2.68	0.52	2.76	0.64	3.05	1.06
TS Avg R^2	0.16	0.71	0.16	0.57	0.16	0.80	0.17	0.71	0.18	0.59
Quarters (T)	65	65	50	50	65	65	65	65	50	50
Portfolios (N)	25	25	25	25	25	25	35	35	35	35

Table 1.13: Intermediary Asset Pricing with Components of $CapFac_{JP}$. Table presents the cross-sectional pricing results for 25 size-and-book-to-market and 10 momentum quarterly portfolios. 35 zombie portfolios, 35 non-zombie portfolios, and 25 Fama–French portfolios are used. The regressions test if the components of $CapFac_{JP}$, the Japanese intermediary capital ratio factor, price the portfolios. $CapFac_{predicted}$ is the component correlated with government risk, and $CapFac_{residual}$ is the component orthogonal to government risk. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium is the annualized increase in expected risk premium associated with a one standard deviation increase in the beta to the intermediary factor component: $\sigma^{\beta} \times \lambda$. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2.

Prices of Risk: $\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f$												
Panel A: ***LevFac*$_{JP}$**												
Bank Dependence Measure	External Finance				Bank Beta				Long-Term Issuer			
	Bank-Dependent		Not Bank-Dep.		Bank-Dependent		Not Bank-Dep.		Bank-Dependent		Not Bank-Dep.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LevFac$_{JP}$	11.787	12.150	3.622	4.624	9.017	12.233	4.453	5.526	14.209	10.676	0.836	1.401
	(2.43)	(2.59)	(0.82)	(1.08)	(2.16)	(2.70)	(1.09)	(1.27)	(2.83)	(2.00)	(0.22)	(0.38)
$Mkt - R_f$		−2.110		0.451		2.032		−0.040		−5.218		0.160
		(−1.12)		(0.22)		(0.82)		(−0.02)		(−2.63)		(0.09)
Ann. Risk Premium	3.02	2.94	0.77	0.96	2.32	2.86	0.89	1.03	3.08	1.93	0.26	0.34
TS GRS p-value	0.16	0.18	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01
MAPE (%)	1.96	1.00	2.33	1.24	2.34	1.25	2.35	1.13	2.13	1.27	2.24	1.34
TS Avg R^2	0.20	0.65	0.12	0.62	0.19	0.63	0.09	0.59	0.11	0.68	0.15	0.60
Quarters (T)	68	68	73	73	79	79	75	75	75	75	79	79
Portfolios (N)	35	35	35	35	35	35	35	35	35	35	35	35
Panel B: ***CapFac*$_{JP}$**												
Bank Dependence Measure	External Finance				Bank Beta				Long-Term Issuer			
	Bank-Dependent		Not Bank-Dep.		Bank-Dependent		Not Bank-Dep.		Bank-Dependent		Not Bank-Dep.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CapFac$_{JP}$	−7.459	−7.523	−12.769	−12.776	−9.645	−9.797	−9.204	−9.143	−10.011	−9.178	−7.955	−7.502
	(−1.44)	(−1.40)	(−2.06)	(−2.08)	(−1.96)	(−1.91)	(−1.58)	(−1.60)	(−2.31)	(−2.16)	(−1.71)	(−1.52)
$Mkt - R_f$		−1.941		−3.734		−1.834		−2.445		−4.153		−2.876
		(−0.84)		(−2.11)		(−0.82)		(−1.24)		(−1.83)		(−2.03)
Ann. Risk Premium	−2.54	−2.56	−3.53	−4.07	−3.50	−3.71	−2.62	−3.19	−3.87	−3.38	−2.80	−2.46
TS GRS p-value	0.32	0.53	0.02	0.04	0.15	0.20	0.05	0.08	0.08	0.15	0.34	0.55
MAPE (%)	2.37	0.88	2.55	0.97	2.73	0.91	2.33	0.93	2.37	1.10	2.45	1.03
TS Avg R^2	0.23	0.66	0.12	0.62	0.24	0.66	0.11	0.57	0.14	0.63	0.16	0.60
Quarters (T)	55	55	53	53	55	55	55	55	53	53	55	55
Portfolios (N)	35	35	35	35	35	35	35	35	35	35	35	35

Table 1.14: Intermediary Asset Pricing of Bank-Dependent Portfolios. Table presents the cross-sectional pricing results for quarterly portfolios: 25 size-and-book-to-market bank-dependent portfolios and 10 momentum bank-dependent portfolios. Firms are classified as bank dependent using three bank dependence measures separately, and bank-dependent portfolios are formed of bank-dependent firms. See the text for additional details on the bank dependence measures and portfolio construction. Not bank-dependent portfolios are formed using the other firms. See the text for additional details on the bank dependence measures and portfolio construction. The regressions test if a Japanese intermediary factor prices the portfolios. *LevFac*$_{JP}$ is the Japanese intermediary leverage factor, and *CapFac*$_{JP}$ is the Japanese intermediary capital ratio factor. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium is the annualized increase in expected risk premium associated with a one standard deviation increase in the beta to the intermediary factor: $\sigma^\beta \times \lambda$. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2.

Prices of Risk: $\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f$						
Panel A: *$LevFac_{predicted}$*						
Bank Dependence Measure	External Finance		Bank Beta		Long-Term Issuer	
	(1)	(2)	(3)	(4)	(5)	(6)
$LevFac_{predicted}$	1.409	0.805	0.737	0.040	1.636	0.732
	(1.62)	(1.42)	(1.21)	(0.07)	(1.83)	(0.84)
$Mkt - R_f$		−3.376		−4.642		−7.172
		(−1.38)		(−3.32)		(−2.77)
Ann. Risk Premium	2.03	1.02	1.45	0.07	2.76	1.16
TS GRS p-value	0.76	0.76	0.01	0.03	0.09	0.15
MAPE (%)	3.12	1.01	3.42	1.11	2.65	1.07
TS Avg R^2	0.03	0.66	0.03	0.65	0.02	0.65
Quarters (T)	65	65	65	65	63	63
Portfolios (N)	35	35	35	35	35	35
Panel B: *$LevFac_{residual}$*						
Bank Dependence Measure	External Finance		Bank Beta		Long-Term Issuer	
	(1)	(2)	(3)	(4)	(5)	(6)
$LevFac_{residual}$	10.529	10.415	11.376	13.006	14.320	10.826
	(2.22)	(2.22)	(2.42)	(2.69)	(2.76)	(1.63)
$Mkt - R_f$		−2.583		−0.664		−7.734
		(−1.40)		(−0.35)		(−2.56)
Ann. Risk Premium	2.49	2.30	2.98	3.04	3.32	2.31
TS GRS p-value	0.28	0.31	0.02	0.01	0.06	0.09
MAPE (%)	1.88	0.98	2.11	0.99	2.19	1.23
TS Avg R^2	0.22	0.66	0.24	0.65	0.13	0.65
Quarters (T)	65	65	65	65	63	63
Portfolios (N)	35	35	35	35	35	35
Panel C: *$LevFac_{predicted}$* and *$LevFac_{residual}$*						
Bank Dependence Measure	External Finance		Bank Beta		Long-Term Issuer	
	(1)	(2)	(3)	(4)	(5)	(6)
$LevFac_{predicted}$	0.170	0.168	−0.666	−0.674	0.539	0.829
	(0.33)	(0.33)	(−1.15)	(−1.16)	(0.84)	(0.91)
$LevFac_{residual}$	9.725	9.706	14.957	15.618	11.570	8.194
	(1.88)	(1.89)	(3.76)	(3.62)	(2.43)	(1.63)
$Mkt - R_f$		−2.431		−1.470		−7.412
		(−1.26)		(−0.93)		(−2.51)
TS GRS p-value	0.66	0.79	0.01	0.02	0.07	0.16
MAPE (%)	3.12	1.01	3.42	1.09	2.76	1.04
TS Avg R^2	0.24	0.67	0.27	0.66	0.15	0.66
Quarters (T)	65	65	65	65	63	63
Porfolios (N)	35	35	35	35	35	35

Table 1.15: Intermediary Asset Pricing of Bank-Dependent Portfolios with Components of $LevFac_{JP}$. Table presents the cross-sectional pricing results for quarterly portfolios: 25 size-and-book-to-market bank-dependent portfolios and 10 momentum bank-dependent portfolios. Firms are classified as bank dependent using three bank dependence measures separately, and bank-dependent portfolios are formed of bank-dependent firms. See the text for additional details on the bank dependence measures and portfolio construction. The regressions test if the components of $LevFac_{JP}$, the Japanese intermediary leverage factor, price the portfolios. $LevFac_{predicted}$ is the component correlated with government risk, and $LevFac_{residual}$ is the component orthogonal to government risk. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium is the annualized increase in expected risk premium associated with a one standard deviation increase in the beta to the intermediary factor component: $\sigma^{\beta} \times \lambda$. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2.

Prices of Risk: $\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f$						
Panel A: $CapFac_{predicted}$						
Bank Dependence Measure	External Finance		Bank Beta		Long-Term Issuer	
	(1)	(2)	(3)	(4)	(5)	(6)
$CapFac_{predicted}$	−2.823	−1.613	−1.476	−0.081	−3.277	−1.467
	(−1.62)	(−1.42)	(−1.21)	(−0.07)	(−1.83)	(−0.84)
$Mkt - R_f$		−3.376		−4.642		−7.172
		(−1.38)		(−3.32)		(−2.77)
Ann. Risk Premium	−2.00	−1.01	−1.44	−0.07	−2.71	−1.15
TS GRS p-value	0.67	0.68	0.01	0.02	0.07	0.11
MAPE (%)	2.78	1.00	3.06	1.05	2.50	1.09
TS Avg R^2	0.03	0.66	0.03	0.65	0.02	0.65
Quarters (T)	65	65	65	65	63	63
Portfolios (N)	35	35	35	35	35	35
Panel B: $CapFac_{residual}$						
Bank Dependence Measure	External Finance		Bank Beta		Long-Term Issuer	
	(1)	(2)	(3)	(4)	(5)	(6)
$CapFac_{residual}$	−7.965	−7.868	−10.360	−11.787	−10.177	−8.326
	(−1.69)	(−1.67)	(−2.37)	(−2.26)	(−2.60)	(−2.23)
$Mkt - R_f$		−2.636		−1.005		−6.150
		(−1.16)		(−0.31)		(−1.99)
Ann. Risk Premium	−2.70	−2.56	−3.56	−3.66	−3.65	−2.72
TS GRS p-value	0.23	0.27	0.02	0.01	0.05	0.07
MAPE (%)	1.88	1.00	2.11	1.00	2.16	1.25
TS Avg R^2	0.18	0.66	0.19	0.65	0.12	0.65
Quarters (T)	65	65	65	65	63	63
Portfolios (N)	35	35	35	35	35	35
Panel C: $CapFac_{predicted}$ and $CapFac_{residual}$						
Bank Dependence Measure	External Finance		Bank Beta		Long-Term Issuer	
	(1)	(2)	(3)	(4)	(5)	(6)
$CapFac_{predicted}$	−0.914	−1.094	0.840	0.482	−1.261	−1.169
	(−0.74)	(−0.87)	(0.52)	(0.34)	(−0.97)	(−0.75)
$CapFac_{residual}$	−6.855	−6.784	−11.675	−11.984	−8.566	−7.555
	(−1.44)	(−1.41)	(−3.00)	(−2.63)	(−2.62)	(−2.27)
$Mkt - R_f$		−1.757		−1.213		−5.553
		(−0.87)		(−0.51)		(−2.12)
TS GRS p-value	0.61	0.69	0.02	0.03	0.08	0.14
MAPE (%)	2.78	0.96	3.06	1.00	2.58	1.04
TS Avg R^2	0.21	0.67	0.22	0.66	0.14	0.66
Quarters (T)	65	65	65	65	63	63
Porfolios (N)	35	35	35	35	35	35

Table 1.16: Intermediary Asset Pricing of Bank-Dependent Portfolios with Components of $CapFac_{JP}$. Table presents the cross-sectional pricing results for quarterly portfolios: 25 size-and-book-to-market bank-dependent portfolios and 10 momentum bank-dependent portfolios. Firms are classified as bank dependent using three bank dependence measures separately, and bank-dependent portfolios are formed of bank-dependent firms. See the text for additional details on the bank dependence measures and portfolio construction. The regressions test if the components of $CapFac_{JP}$, the Japanese intermediary capital ratio factor, price the portfolios. $CapFac_{predicted}$ is the component correlated with government risk, and $CapFac_{residual}$ is the component orthogonal to government risk. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium is the annualized increase in expected risk premium associated with a one standard deviation increase in the beta to the intermediary factor component: $\sigma^{\beta} \times \lambda$. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2.

	News-Implied Volatility Indexes				Risk 1A Long-Short Portfolio Returns				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	GovFac	*GovFac*	*GovFac*	*GovFac*	*GovFac*	*GovFac*	*GovFac*	*GovFac*	*GovFac*
$-1\times$ $NVIX$	0.049***								
	(9.00)								
$-1\times$Government		0.788***							
		(6.97)							
$-1\times$Intermediation			0.284***						
			(6.92)						
$-1\times$Stock Markets				0.361***					
				(6.26)					
Taxes					0.012*				
					(2.09)				
Regulations						0.013*			
						(2.13)			
Economic Conditions							0.014*		
							(2.32)		
Bank Regulations								0.011	
								(1.70)	
Credit Market									0.011
									(1.69)
Constant	1.514***	0.768***	0.670***	0.871***	0.120**	0.120***	0.119**	0.125***	0.123***
	(11.06)	(8.57)	(9.42)	(7.96)	(3.34)	(3.37)	(3.35)	(3.52)	(3.41)
N	147	147	147	147	160	160	160	160	160
Adj. R^2	0.53	0.22	0.32	0.22	0.02	0.02	0.02	0.01	0.01

Table 1.17: Correlation of the U.S. Government Risk Factor with Other Government Risk Measures. Table presents time-series regressions at the monthly level. The dependent variable is the government risk factor. The independent variables are other government risk measures, including news-implied volatility indexes from Manela and Moreira (2017) and Risk 1A long-short portfolio returns from Ross (2019). t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Sample	All Commercial Banks		Top 50 Commercial Banks	
	(1) Return	(2) Return	(3) Return	(4) Return
$GovFac_{synthetic}$	0.018***	0.012***	0.017***	0.008*
	(10.40)	(7.29)	(4.72)	(2.52)
$GovFac_{synthetic} \times \mathbb{I}(\text{WSJ})$	0.007	0.008	0.007	0.008
	(0.99)	(1.32)	(0.93)	(1.22)
$GovFac_{synthetic} \times \mathbb{I}(\text{Post})$	−0.022***	−0.025***	−0.028**	−0.024*
	(−5.82)	(−6.63)	(−2.87)	(−2.50)
$GovFac_{synthetic} \times \mathbb{I}(\text{WSJ}) \times \mathbb{I}(\text{Post})$	0.040**	0.040***	0.046**	0.037**
	(3.29)	(3.53)	(3.06)	(2.62)
$\mathbb{I}(\text{Post})$	0.070***	0.070***	0.068*	0.081*
	(5.62)	(4.84)	(1.96)	(2.38)
$\mathbb{I}(\text{WSJ})$	0.000	−0.001	0.005	0.005
	(0.01)	(−0.15)	(0.50)	(0.56)
$\mathbb{I}(\text{WSJ}) \times \mathbb{I}(\text{Post})$	−0.008	−0.002	0.004	0.001
	(−0.56)	(−0.15)	(0.22)	(0.04)
$Mkt - R_f$		0.605***		1.041***
		(258.53)		(196.14)
Size		0.000***		0.000***
		(4.27)		(4.06)
Assets		−0.000**		−0.000
		(−3.24)		(−1.86)
Constant	−0.033	0.006	−0.044	0.007
	(−0.25)	(0.05)	(−0.37)	(0.07)
N	3,935,268	3,572,187	598,452	598,452
Adj. R^2	0.00	0.05	0.00	0.20
Year FE	Yes	Yes	Yes	Yes
SIC FE	Yes	Yes	Yes	Yes

Table 1.18: Beta of U.S. Commercial Banks to the Synthetic U.S. Government Risk Factor, Robustness. Table presents time-series regressions at the daily level. The dependent variable is return in percent. Independent variables are the synthetic U.S. government risk factor, $GovFac_{synthetic}$, the factor interacted with indicator variables, and controls for the indicator variables, the market return, the bank's market capitalization, and the bank's assets. See the text for additional details on $GovFac_{synthetic}$. $\mathbb{I}(\text{WSJ}) = 1$ if the bank is one of the 11 banks cited as too big to fail by *The WSJ*, and 0 otherwise. $\mathbb{I}(\text{Post}) = 1$ if the date is after September 20, 1984, and 0 otherwise. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel A: All Commercial Banks

Period	National and State Commercial Banks Full (1) $\beta_{GovFac_{syn.}}$	National and State Commercial Banks 4 Year (2) $\beta_{GovFac_{syn.}}$	National Commercial Banks Full (3) $\beta_{GovFac_{syn.}}$	National Commercial Banks 4 Year (4) $\beta_{GovFac_{syn.}}$	State Commercial Banks Full (5) $\beta_{GovFac_{syn.}}$	State Commercial Banks 4 Year (6) $\beta_{GovFac_{syn.}}$
$\mathbb{I}$(WSJ)	−0.545	−7.520**	0.045	−6.609**	−2.207	−5.522
	(−0.84)	(−2.88)	(0.06)	(−3.02)	(−1.36)	(−0.43)
$\mathbb{I}$(Post)	1.462**	0.353	1.094	0.341	1.441	0.316
	(2.91)	(0.50)	(1.64)	(0.38)	(1.87)	(0.28)
$\mathbb{I}$(WSJ) × $\mathbb{I}$(Post)	3.820***	13.798***	2.044	13.465**	9.720***	15.483**
	(3.69)	(3.72)	(1.80)	(2.72)	(3.92)	(2.61)
Constant	−1.864	−2.046*	−1.977	−3.304**	1.556	−1.496
	(−1.45)	(−2.02)	(−1.47)	(−3.17)	(1.00)	(−1.04)
N	40,966	5,989	21,084	3,492	19,882	2,497
Adj. R^2	0.03	0.04	0.06	0.06	0.03	0.02
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SIC FE	Yes	Yes	N/A	N/A	N/A	N/A

Panel B: Restricted to Large Banks

Period	National and State Commercial Banks Full (1) $\beta_{GovFac_{syn.}}$	National and State Commercial Banks 4 Year (2) $\beta_{GovFac_{syn.}}$	National Commercial Banks Full (3) $\beta_{GovFac_{syn.}}$	National Commercial Banks 4 Year (4) $\beta_{GovFac_{syn.}}$	State Commercial Banks Full (5) $\beta_{GovFac_{syn.}}$	State Commercial Banks 4 Year (6) $\beta_{GovFac_{syn.}}$
$\mathbb{I}$(WSJ)	−0.387	−4.342	0.299	−4.106	−3.168	8.853
	(−0.55)	(−1.74)	(0.38)	(−1.95)	(−1.54)	(0.46)
$\mathbb{I}$(Post)	2.262**	0.098	1.562	0.417	1.826	−0.930
	(2.69)	(0.08)	(1.76)	(0.36)	(0.86)	(−0.28)
$\mathbb{I}$(WSJ) × $\mathbb{I}$(Post)	2.726*	12.249**	1.049	10.956*	9.421**	14.846*
	(2.49)	(3.23)	(0.88)	(2.20)	(3.20)	(2.20)
Constant	−2.525	−1.528	−2.546	−3.181*	0.955	1.084
	(−1.85)	(−1.18)	(−1.85)	(−2.41)	(0.58)	(0.25)
N	11,649	2,516	8,783	1,811	2,866	705
Adj. R^2	0.09	0.08	0.11	0.10	0.05	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SIC FE	Yes	Yes	N/A	N/A	N/A	N/A

Table 1.19: Difference-in-difference Regression of Synthetic U.S. Government Risk Factor Betas. Table presents time-series regressions of monthly bank betas. The dependent variable is the bank's beta to synthetic U.S. government risk factor, estimated monthly using daily data. Independent variables are indicator variables and controls for the bank's monthly market beta, market capitalization, and assets. $\mathbb{I}(\text{WSJ}) = 1$ if the bank is one of the 11 banks cited as too big to fail by *The WSJ*, and 0 otherwise. $\mathbb{I}(\text{Post}) = 1$ if the date is after September 20, 1984, and 0 otherwise. The SIC code identifies national and state commercial banks. Regression is estimated over the full period and during a window of four years before and four years after the event date. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	National and State Commercial Banks		National Commercial Banks		State Commercial Banks	
Period	Full	4 Year	Full	4 Year	Full	4 Year
	(1)	(2)	(3)	(4)	(5)	(6)
	$\beta_{GovFac_{syn.}}$	$\beta_{GovFac_{syn.}}$	$\beta_{GovFac_{syn.}}$	$\beta_{GovFac_{syn.}}$	$\beta_{GovFac_{syn.}}$	$\beta_{GovFac_{syn.}}$
$\mathbb{I}$(WSJ)	−0.108	−3.494	0.257	−1.665	−1.820	-19.801^{*}
	(−0.09)	(−1.45)	(0.34)	(−0.72)	(−0.79)	(−2.02)
$\mathbb{I}$(Post, Placebo)	−1.415	−1.210	−1.704	−1.924	−1.531	−0.420
	(−0.85)	(−1.02)	(−1.12)	(−1.24)	(−0.85)	(−0.22)
$\mathbb{I}$(WSJ) $\times$ $\mathbb{I}$(Post, Placebo)	3.079^{*}	2.486	1.686	5.201	8.319^{**}	3.805
	(2.27)	(0.86)	(1.48)	(1.26)	(2.88)	(0.83)
Constant	−1.866	-1.982^{*}	−1.978	-3.686^{**}	1.551	−1.914
	(−0.43)	(−2.01)	(−1.47)	(−2.89)	(1.00)	(−1.67)
N	40,966	5,428	21,084	3,198	19,882	2,230
Adj. R^2	0.03	0.05	0.06	0.08	0.03	0.03
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SIC FE	Yes	Yes	N/A	N/A	N/A	N/A

Table 1.20: Difference-in-difference Regression of Synthetic U.S. Government Risk Factor Betas, Placebo Test of 1 Year Earlier. Table presents time-series regressions of monthly bank betas. The dependent variable is the bank's beta to synthetic U.S. government risk factor, estimated monthly using daily data. Independent variables are indicator variables and controls for the bank's monthly market beta, market capitalization, and assets. $\mathbb{I}(\text{WSJ}) = 1$ if the bank is one of the 11 banks cited as too big to fail by *The WSJ*, and 0 otherwise. $\mathbb{I}(\text{Post, Placebo}) = 1$ if the date is after September 20, 1983, and 0 otherwise. The SIC code identifies national and state commercial banks. Regression is estimated over the full period and during a window of four years before and four years after the event date. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1)	(2)	(3)
	$\beta_{GovFac_{syn.}}$	$\beta_{GovFac_{syn.}}$	$\beta_{GovFac_{syn.}}$
$\mathbb{I}$(WSJ)	14.642***	−0.211	1.627
	(13.75)	(−0.18)	(1.20)
$\mathbb{I}$(Post)		−16.595***	−6.983***
		(−24.76)	(−5.26)
$\mathbb{I}$(WSJ) × $\mathbb{I}$(Post)		22.140***	17.259***
		(14.81)	(11.43)
β_{Market}			−4.889*
			(−1.98)
Size			0.000
			(1.08)
Assets			−0.000***
			(−12.18)
Constant	−12.828***	−0.783***	1.986
	(−27.29)	(−3.69)	(1.61)
N	23,117	23,117	23,117
Adj. R^2	0.00	0.01	0.04

Table 1.21: Beta Comparision between Large Banks Near the Too Big to Fail Cutoff. Table presents time-series regressions of monthly bank betas. The dependent variable is the bank's beta to synthetic U.S. government risk factor, estimated monthly using daily data. Independent variables are indicator variables and controls for the bank's monthly market beta, market capitalization, and assets. $\mathbb{I}(\text{WSJ}) = 1$ if the bank is one of the 11 banks cited as too big to fail by *The WSJ*, and 0 otherwise. $\mathbb{I}(\text{Post}) = 1$ if the date is after September 20, 1984, and 0 otherwise. Sample is restricted to commercial banks larger than Continental Illinois and within the largest 25 banks. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Treatment Group	Big Three					Autos				
	(1) Return	(2) Return	(3) Return	(4) Return	(5) Return	(6) Return	(7) Return	(8) Return	(9) Return	(10) Return
GovFac	0.985***	0.119***	0.212***	0.143***	0.458***	0.985***	0.118***	0.210***	0.142***	0.458***
	(70.53)	(8.90)	(13.79)	(6.42)	(14.78)	(70.53)	(8.78)	(13.69)	(6.40)	(14.75)
GovFac × 𝕀(Treated)		1.166**	1.172**	−0.051	−0.052		0.717***	0.716***	0.153	0.192
		(2.59)	(2.60)	(−0.10)	(−0.10)		(3.30)	(3.29)	(0.65)	(0.54)
GovFac × 𝕀(Post)				−0.042	−0.355***				−0.044	−0.357***
				(−1.45)	(−10.03)				(−1.51)	(−10.07)
GovFac × 𝕀(Treated) × 𝕀(Post)				1.982*	1.983*				0.982**	0.938
				(2.54)	(2.47)				(2.61)	(1.95)
Constant	0.026***	0.031***	0.186***	0.030***	0.169***	0.026***	0.031***	0.186***	0.030***	0.169***
	(18.94)	(23.58)	(7.04)	(19.81)	(6.38)	(18.94)	(23.56)	(7.04)	(19.80)	(6.38)
N	10,803,752	10,803,752	10,803,752	10,803,752	10,803,752	10,803,752	10,803,752	10,803,752	10,803,752	10,803,752
Adj. R^2	0.00	0.10	0.10	0.10	0.10	0.00	0.10	0.10	0.10	0.10
Year FE	No	No	Yes	No	Yes	No	No	Yes	No	Yes
SIC FE	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Incl. Treatment Indicator	No	Yes	Yes	No	No	No	Yes	Yes	No	No
Incl. Market	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes

Table 1.22: Beta of U.S. Auto Companies to the U.S. Government Risk Factor, Robustness. Table presents time-series regressions at the daily level. The dependent variable is return in percent. Independent variables are the U.S. government risk factor, *GovFac*, the factor interacted with indicator variables, and controls for the market return. See the text for additional details on *GovFac*. $\mathbb{I}$(Treated) is the treatment indicator. In columns 1 to 5, $\mathbb{I}(\text{Treated}) = 1$ if the firm is one of the Big Three automakers, and 0 otherwise. In columns 6 to 10, $\mathbb{I}(\text{Treated}) = 1$ if the firm is an automaker, and 0 otherwise. $\mathbb{I}(\text{Post}) = 1$ if the date is after December 19, 2008, and 0 otherwise. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

1.8.5 Appendix Figures

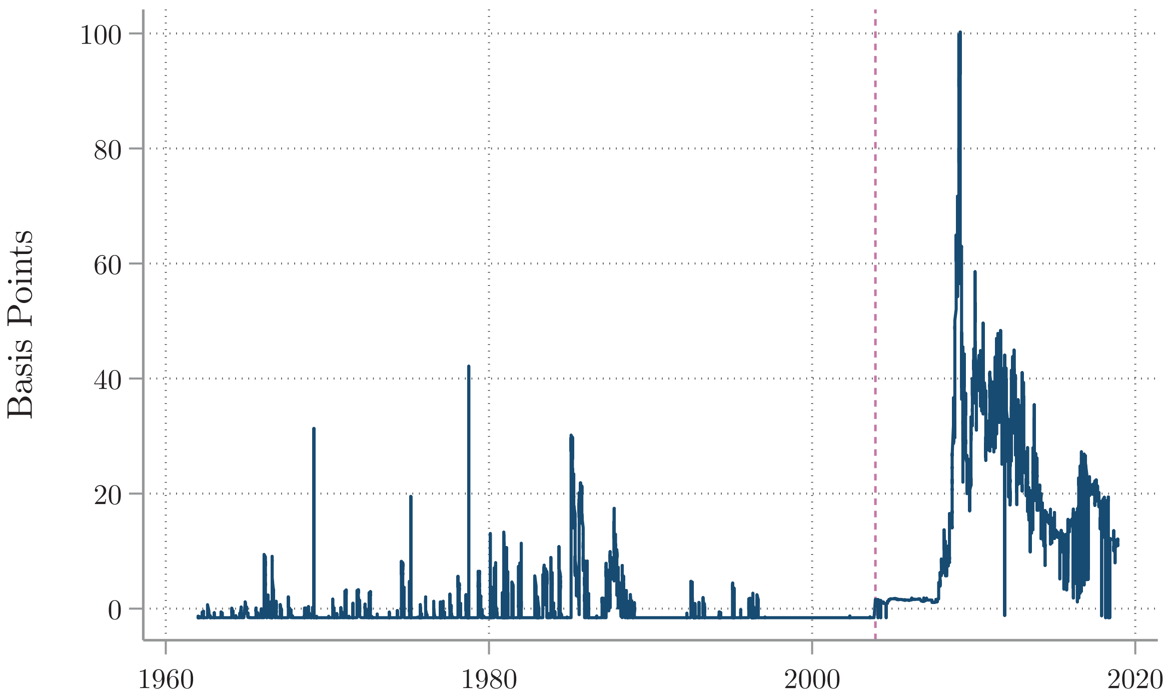


Figure 1.11: Synthetic U.S. Sovereign CDS Spread. Figure shows the par-equivalent CDS spread, demeaned and scaled, and spliced with the U.S. sovereign CDS spread. See Appendix 1.8.1 for details on the construction.

Chapter 2

Zombie Asset Pricing

2.1 Introduction

Beginning in the 1990s, Japanese banks restructured loans to insolvent borrowers—zombie firms—to avoid recognizing non-performing loans and their associated capital write-down. Banks rolled over loans many times in an environment of regulatory forbearance, leading to distorted macro outcomes. I show zombies also affects asset pricing premiums, and correcting for *zombie-ness* revives momentum in Japan.

Compared to international counterparts, momentum in Japan is viewed as too low. Japan's low momentum is a long-cited concern leading some to question whether momentum is more generally a spurious result. I examine the effect of zombies on Japanese momentum and value five ways.

First, I create zombie-adjusted value and momentum factors and show these premiums fall in line with global averages. The momentum premium and Sharpe ratio in Japan double when I exclude zombies. Excising zombies also reduces the value premium toward the global average. Combined, Japanese momentum and value are consistent with other developed markets' premiums only after controlling for zombies, and the two anomalies retain a strong negative correlation.

Second, I use syndicated loan data to identify companies that borrow from forbearance-inclined banks. Companies that borrow only from forbearance-inclined banks are more likely to have the opportunity to become zombies. I show that firms with international lead arrangers have value and momentum premiums near international equity premiums, while firms with more forbearance-inclined lenders have value and momentum premiums like zombies.

Third, I run cross-sectional pricing tests to show that momentum commands a positive price of risk only after adjusting for zombies. I construct zombie-adjusted factors in two ways: by controlling for zombies and by dropping zombies. Firms fail to earn compensation for loading on Japan's unadjusted momentum factor, but the zombie-adjusted momentum factor prices Japanese equity portfolios. The factors' zombie-adjustment also helps align portfolios' returns with betas. Fourth, I show that the zombie-adjusted momentum factor is not spanned by other factors, including any standard quality factors. Other factors span vanilla momentum without the zombie adjustment.

Finally, I argue that momentum is low because of zombies' dependence on regulatory forbearance and banks. The syndicated loan lending results, an event study, and time-series regressions support the argument. An event study around four financial institutions' failures indicates that zombies faced lower abnormal returns than non-zombies after shocks to the banking system. Time-series regressions demonstrate that zombies have strong bank beta, and within zombies, zombie losers have particularly high bank beta. When banks have strong returns, zombie losers also have strong returns, pushing down zombie momentum and momentum overall. Non-zombie winners and losers have similar bank beta, so good bank returns do not have a meaningful impact on non-zombie momentum. I show that the best 20 months of bank returns—5.5% of the sample—account for nearly 40% of the difference between zombie momentum and non-zombie momentum. The zombie-adjustment also removes the covariance between momentum and government risk.

Section 3.4 describes the data and factor construction. Section 2.3 presents the results. Section 3.6 concludes.

Related Literature

This paper contributes to the literature on zombie credit. In Japan, the lost decade of the 1990s turned into more than two lost decades because of low productivity growth (Hayashi and Prescott, 2002). Underlying the productivity problems were zombies. Japanese banks evergreened loans to weak firms to avoid losses on their bank balance sheets, with more troubled firms more likely to receive bank credit (Peek and Rosengren, 2005). Caballero et al. (2008) show that zombies have negative externalities for healthy firms because zombies reduce the profits of healthy firms and lower investment and employment growth for non-zombies. Zombies had large macro effects on Japan's productivity growth and altered the competitive process.

Zombies are not unique to Japan. Andrews et al. (2017) document an increase of zombie firms in OECD countries since the mid-2000s, and they show that the zombies' survival attenuates labor productivity growth. Banerjee and Hofmann (2018) show a rise of zombies in 14 advanced economies since the late 1980s, and they attribute the increase to reduced financial pressure in the form of lower interest rates. Acharya et al. (2020) show how zombie credit has a disinflationary effect by creating excess production capacity, increasing supply, and lowering prices. Schivardi et al. (2019), Bonfim et al. (2020), and Blattner et al. (2019) show the role of bank lending relationships to zombie firms in Italy and Portugal.

My paper also adds to the literature on value and momentum. Asness et al. (2013a) find a robust negative correlation between value and momentum across many markets and asset classes. The low momentum effect in Japan leads some to hesitate including momentum in asset pricing models and to question whether momentum is a spurious result more generally. Asness (2011) shows that the pairing of low momentum with the strong outperformance of value in Japan highlights the negative covariance of value and momentum in Japan to explain the poor performance of momentum.

2.2 Data

Japanese Data I use Japanese market data and accounting data from Datastream and Worldscope. The data cover 1979 to 2018 and consist of the universe of Japanese stocks in Datastream and Worldscope. I restrict my sample to companies with a book value in the previous six months and at least 12 months of return history, and I exclude financials (including REITs) and stocks that have a share price less than $1 at the start of each month.

To compare my results to international value and momentum premiums, I follow Asness et al. (2013a) and restrict the data to a sample of liquid stocks. Each month, I sort stocks by market capitalization in descending order. Starting with the largest market capitalization stock, I include all stocks until the cumulative market capitalization is 90% of the total market capitalization for that month.

Identifying Zombies I identify zombies following Caballero et al. (2008): I compare a firm's actual interest payment, $R_{i,t}$, to an estimated lower-bound $R^{\star}_{i,t}$. The lower-bound stands for the interest payments a firm i could expect if it borrowed at no spread to the prime rate at time t:

$$R^{\star}_{i,t} = r^{s}_{t-1} S_{i,t-1} + \left(\frac{1}{5} \sum_{j=1}^{5} r^{\ell}_{t-j} \right) L_{i,t-1} \tag{2.1}$$

where $S_{i,t}$ is short-term debt and $L_{i,t}$ is long-term debt, and r^{s}_{t} and r^{ℓ}_{t} are the Bank of Japan's short-term and average long-term prime rates, which reflect the prime lending rate at which principal banks lend.

I construct the interest-rate gap, $X_{i,t}$, as the difference between the actual interest payment and the lower bound, scaled by the total debt:

$$X_{i,t} \equiv \frac{R_{i,t} - R^{\star}_{i,t}}{B_{i,t-1}} = r_{i,t} - r^{\star}_{i,t}. \tag{2.2}$$

In principle, only the highest-quality companies should borrow at effective rates near the prime rate, and most corporate borrowers would expect to borrow at a nontrivial spread to the prime rate. Following Caballero et al. (2008), I define companies with an interest-rate gap below 0 as *crisp* zombies, and companies borrowing near the prime rate—those with an interest-rate gap of 0 to 50 bps—as *fuzzy* zombies. I lag the interest-rate gap by six months to match the accounting data lag and ensure the balance sheet data are in the investors' information set.

Zombies-ness is persistent, and switches from zombie to non-zombie or vice versa occur roughly 1.5% of the time. The interest-rate gap is uncorrelated with firm size. Before removing small and illiquid stocks to restrict the sample to a liquid sample, size has a correlation of −0.1% with the interest-rate gap, a correlation of 4.8% with an indicator for crisp zombie, and a correlation of 3.8% with an indicator for crisp or fuzzy zombie. Cleaning the dataset to the liquid set of stocks increases the share of zombies from 20% to 48%.

Value and Momentum Premium and Strategy Factors Value and momentum premium and strategy factors are created using sorts based on the underlying signals. For value, I use the ratio of the book value of equity to the market value of equity, where I lag book value by six months. For momentum, I sort based on the past 12-month cumulative return, with the most recent month skipped to account for the 1-month short-term reversal. I construct premium and strategy factors in the same way as Asness et al. (2013a).

The value premium factor is constructed by sorting the liquid set of stocks into three equal-sized groups (called High, Middle, and Low) based on book-to-market. The value premium is the value-weighted return of the High portfolio minus the Low portfolio. The momentum premium is created analogously, sorting based on past return rather than book-to-market.

The strategy factors use zero-cost, signal-weighted portfolios, which dampens the impact of outliers. The strategy factor return for each signal $S \in (\text{value}, \text{momentum})$ is

$$r_t^S = \sum_i w_{it}^S r_{it} \tag{2.3}$$

where the weight for each security $i = 1, \ldots, N$ at time t is

$$w_{it}^S = c_t \underbrace{\left(rank(S_{it}) - \frac{1}{N} \sum_i rank(S_{it}) \right)}_{x_{it}} \tag{2.4}$$

where the weights sum to zero for each period and c_t is a scaling factor to make the portfolio scaled to one dollar long and one dollar short.

Zombie-Adjusted Value and Momentum Factors I adjust the standard value and momentum factors, *HML* and *WML*, to account for zombies. I create HML_{ZA} and WML_{ZA}, the zombie-adjusted factors, in two ways: first, by dropping zombies from the sample before forming the factors using the conventional method; and second, by triple-sorting to control for zombie-ness. Each of the zombie-adjusted factors can be constructed with zombies as crisp and fuzzy varieties or as crisp zombies alone. Either process yields similar asset pricing results.

First, I drop zombies from the sample and split the data into equal groups by value (High, Middle, Low) and size (Small, Big). I construct six double-sorted portfolios: High/Big, High/Small, Middle/Big, Middle/Small, Low/Big, Low/Small. I use the portfolio returns to calculate the zombie-adjusted value factor according to the following equation:

$$HML_{ZA} = \frac{\text{High/Small} + \text{High/Big}}{2} - \frac{\text{Low/Small} + \text{Low/Big}}{2}. \tag{2.5}$$

I construct WML_{ZA} using the same method. After dropping zombies, the data are split into equal groups by past returns (Winner, Middle, Loser) and size (Small, Big). I form six double-sorted portfolios and calculate the zombie-adjusted momentum factor:

$$WML_{ZA} = \frac{\text{Winner/Small} + \text{Winner/Big}}{2} - \frac{\text{Loser/Small} + \text{Loser/Big}}{2}. \tag{2.6}$$

Second, I keep zombies in the data and control for them in the factor creation. I sort the data into equal groups by value (H, M, L), momentum (W, M, L), size (S, B), and zombie-ness (Z, N). I form triple-sorted portfolios using the value, size, and zombie-ness sorts; and I form triple-sorted portfolios using the momentum, size, and zombie-ness sorts. I use the triple-sorted portfolios to construct the zombie-adjusted factors:

$$HML_{ZA} = \frac{\text{H/S/Z} + \text{H/S/N} + \text{H/B/Z} + \text{H/B/N}}{4} - \frac{\text{L/S/Z} + \text{L/S/N} + \text{L/B/Z} + \text{L/B/N}}{4} \tag{2.7}$$

and

$$WML_{ZA} = \frac{\text{W/S/Z} + \text{W/S/N} + \text{W/B/Z} + \text{W/B/N}}{4} - \frac{\text{L/S/Z} + \text{L/S/N} + \text{L/B/Z} + \text{L/B/N}}{4}. \tag{2.8}$$

Syndicated Loans Data I use data from Loan Pricing Corporation (LPC) Dealscan, which has data on Japanese firms' syndicated loans beginning in 1988, to establish lending relationships between banks and borrowers. I match the Datastream tickers to Compustat data using ISIN, and I link the Compustat data to Dealscan data using the Roberts Dealscan-Compustat Linking Database, which links the data at the facility, or loan tranche, level. The method matches 38% of Japanese loans to a specific Datastream ticker, and 59% of my liquid Datastream data has at least one syndicated loan.

I use the Dealscan data to classify the lead arranger for each loan, and I sort my data based on firms with only Japanese lead arrangers and firms that have international lead arrangers. There are multiple syndicated loans for many firms, and I consider the Japanese borrower-lender relationship to start from the earliest syndicated loan date and calculate value and momentum for firms with only Japanese lead arrangers. Over the same period, I calculate value and momentum for firms that have international lead arrangers.

I also classify firms with capital injection lead arrangers based on the earliest syndicated loan date, and I calculate value and momentum for those firms and all the remaining firms over the same period.

2.3 Results

In Japan, zombies are widespread, value is high, and momentum is low. I show that zombies impact Japanese value and momentum in five ways. First, adjusting for zombies transforms the Japanese premiums to look more similar to global value and momentum premiums. Second, syndicated loan lending relationships show that firms with forbearance-inclined lenders have value and momentum premiums like zombies. Firms with less forbearance-inclined bank lenders have value and momentum premiums near international equity premiums. Third, cross-sectional asset pricing tests indicate that momentum earns a positive price of risk only after adjusting for zombies. Fourth, I show that a momentum factor is unspanned only after adjusting for zombies. Last, I argue that regulatory forbearance and the relationship between zombies and their bank lenders drive low momentum using event studies and time-series regressions.

2.3.1 Zombie-Adjusted Value and Momentum

Table 2.1 shows the returns to the value and momentum premiums and the signal-weighted strategies, calculated separately for the full dataset of liquid stocks and with zombies removed. All returns are in annualized terms.[1] In the full data, Japan's momentum premium is 0.96%, and the value premium is 11.45%. The value premium and strategy are statistically significant, while the momentum counterparts are statistically indistinguishable from zero.

Removing crisp zombies doubles the momentum premium and Sharpe ratio and nearly doubles the momentum strategy return and Sharpe ratio. Momentum grows even more after dropping both crisp and fuzzy zombies. Value, in turn, decreases with zombies removed. The premiums maintain their strong negative correlation even after removing zombies.[2]

Japan's anomalies line up with the global average after I control for zombies. Table 2.2 compares value

[1]See Section 3.4 for details on signal-weighted strategy construction.

[2]See Appendix 2.7.1 for additional details.

and momentum in Japan to the premiums and strategies abroad. The Global Average is the equal-weighted mean of the premium and strategy in the U.S., the U.K., and continental Europe; the Global Stocks row shows the value and momentum strategy factors as calculated by Asness et al. (2013a). Momentum jumps from about 10% of the global numbers to 40% when adjusting for zombies. Value also moves closer to global figures, declining from more than three times the global average. Figure 2.1 shows this graphically. Value in Japan is exceptionally large, while momentum is exceptionally low, both in average returns and Sharpe ratios. The asset pricing premiums place Japan in the bottom-right of the graph for both the premium and strategy. All the other countries are above the 45-degree line, meaning that momentum exceeds value. After adjusting for zombies, Japan's strategy and premium factors move toward the 45-degree line.

2.3.2 Syndicated Loan Lending Relationships

Zombies arise from regulatory forbearance in Japan, so zombies' subsidized credit should come from Japanese lenders. International lenders like U.S.-based J.P. Morgan have neither the incentive nor the implicit government support to lend at subsidized rates to Japanese firms. Thus, comparing firms with only Japanese lenders to firms with international lenders classifies firms using a related but distinct zombie-ness measure. Using syndicated loan data, I classify firms by their lending relationships. I find that firms with forbearance-inclined lenders drive Japan's high value and low momentum premiums.

Syndicated loans are large loans provided by a group of lenders. Typically, one bank is the lead arranger; that bank is often the largest lender in the group and plays a leading role in negotiating the contract. I sort my data based on firms with only Japanese lead arrangers and firms with international lead arrangers and calculate the value and momentum premiums for those companies.[3] Separately, I identify firms that borrowed from one of the 21 financial institutions that received capital injections from the Japanese government in March 1998 based on the Financial Function Stabilization Act.[4] I expect that banks that needed capital injections were those most likely to forbear on their loans.

Table 2.3 shows the value and momentum premium for these subsets. Firms with only Japanese lead arrangers have negative momentum, and value is double the global average. In contrast, firms with international lead arrangers have a momentum Sharpe ratio of more than quadruple the full-sample premium. Classifying firms based on their lead arrangers' capital injection status gives comparable results: firms without capital injections, who presumably have less forbearance, have lower value and higher momentum.

[3]See Section 3.4 for data details.

[4]These 21 capital injections totaled ¥1.8 trillion, with most of the banks taking ¥100 billion in subordinated debt, the amount the healthiest bank (Bank of Tokyo Mitsubishi) was willing to take. But this amount was "far less" than the amount needed to restore capital for most banks (Hoshi and Kashyap, 2010), and there was price discrimination with each bank having a different interest rate.

2.3.3 Zombie-Adjusted Cross-Sectional Pricing

I show that a zombie-adjusted momentum factor helps explain the cross-section of expected returns for Japanese equity portfolios. I adjust the standard value and momentum factors, *HML* and *WML*, to account for zombies in two ways. First, I create zombie-adjusted factors HML_{ZA} and WML_{ZA} by dropping zombies from the sample before forming the factors using the conventional method. Second, I triple-sort to control for zombie-ness.[5]

I calculate the price of risk for a risk factor using the portfolio returns and a two-step procedure. First, I estimate each portfolio i's beta to the risk factor using time-series regressions of each portfolio's excess return on the factor:

$$R^e_{i,t} = \alpha_i + \beta'_{i,f}\mathbf{f}_t + \varepsilon_{i,t},\ i = 1, \ldots, N,\ t = 1, \ldots, T, \tag{2.9}$$

where $\mathbf{f}_t$ is a vector of risk factors. Then I run a cross-sectional regression of portfolio excess returns on the betas estimated in Equation 2.9:

$$\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f + \xi_i,\ i = 1, \ldots, N. \tag{2.10}$$

I use the two-step procedure and $\mathbf{f} = [Mkt - Rf, SMB, HML, WML]$ or $\mathbf{f} = [Mkt - Rf, SMB, HML_{ZA}, WML_{ZA}]$ to calculate the factors' prices of risk. The regressions begin in November 1990, the first observation for *WML* in Japan.

Table 2.4 shows the prices of risk from cross-sectional regressions of 25 size-and-book-to-market portfolios in Japan. The first three columns use unadjusted factors. Column 1 is CAPM; column 2 is the Fama–French 3-factor model; column 3 is the Carhart 4-factor model, which includes momentum, *WML*. The results with the unadjusted factors show that momentum does not have a significant price of risk. I use zombie-adjusted factors HML_{ZA} and WML_{ZA} in the remaining columns. In columns 4 to 7, I remove zombies to construct the factors, and in columns 8 to 11, I triple-sort zombies to construct the factors.

Adjusting for zombies recovers compensation for momentum risk. The price of risk for WML_{ZA} is positive and significant in the cross-sectional regressions. The time-series results are similar for the Fama–French factors and the zombie-adjusted factors. The mean average pricing errors are similar, and the GRS p-values tend to be large and fail to reject the null that the alphas are jointly zero; thus, in both cases, we fail to reject the model.

Adjusting for zombies aligns the portfolios' average excess returns with the portfolios' betas to value and

[5] See Section 3.4 for details.

momentum factors. Figure 2.2 shows the portfolios' betas to value and momentum factors. The betas to the Fama–French momentum factor fluctuate only slightly between portfolios, even though the portfolios' expected returns vary substantially. Betas to zombie-adjusted factors appear to capture the variation: the betas monotonically increase, moving from growth to value stocks within a size group. If the price of risk is positive and constant, as estimated in cross-sectional regressions, the betas should vary as expected returns increase. The zombie adjustment slightly dampens value betas.

Figure 2.3 plots the portfolios' betas to the momentum and value factors against the portfolios' average excess returns. The betas to the zombie-adjusted momentum factor line up better with expected returns. The slope is statistically indistinguishable from zero using the Fama–French momentum factor WML to calculate the portfolios' betas. But the betas to WML_{ZA} have a significantly positive slope.[6]

2.3.4 Spanning Tests

Spanning tests show whether a factor's economic content is contained in a linear combination of other factors. Table 2.5 shows the factor spanning tests. Each row of the table is a separate regression. Panel A shows the spanning tests for the unadjusted Fama–French factors. The results show that other factors span momentum, implying that momentum does not need to be included in the model. Panel B uses zombie-adjusted factors HML_{ZA} and WML_{ZA}, constructed by dropping crisp zombies. Panel C drops crisp and fuzzy zombies. Panel D uses the triple-sort method discussed in Section 3.4 and controls for crisp zombies, and Panel E triple-sorts crisp and fuzzy zombies.

The significant intercept on WML_{ZA} in all four panels shows that other factors do not span zombie-adjusted momentum, and the results support the inclusion of momentum in the model. The spanning tests also highlight the negative covariance between value and momentum: the zombie adjustment does not affect the negative covariance between value and momentum.

Quality Caballero et al. (2008) classify zombie firms based on their interest-rate gap rather than by operating characteristics like productivity or profitability metrics. They show that zombies tend to be low productivity firms. I show that common quality factors in Japan do not span zombie-adjusted factors.

Table 2.6 adds the three Japanese quality factors—RMW (Robust Minus Weak), QMJ (Quality Minus Junk) and BAB (Betting Against Beta)—individually to the spanning tests. The table shows intercepts and t-statistics from a regression of the labeled factor on the other four factors in the panel and column. For example, the first coefficient is the intercept from the regression of the market factor on SMB, HML, WML, and RMW. The last coefficient is the intercept from the regression of BAB on the market factor, SMB,

[6] The slope is significant regardless of whether I drop zombies or triple-sort zombies in the construction of WML_{ZA}.

HML_{ZA}, and WML_{ZA}, where HML_{ZA} and WML_{ZA} are constructed by triple-sorting crisp and fuzzy zombies. Panel A shows that the other factors span the unadjusted Japanese momentum factor. Panels B, C, D, and E use different forms of the zombie-adjusted value and momentum factors to show that zombie-adjusted momentum, WML_{ZA}, is not spanned by quality.

The results show that controlling for quality does not change the spanning results. Controlling for zombies is not just a reincarnation of controlling for the quality or profitability anomaly.

2.3.5 Zombie Lending Drives Low Momentum

In this section, I argue that the relationship between zombies and their bank lenders drives low momentum and high value in Japan. The syndicated loan results in Section 2.3.2—which shows that firms with forbearance-inclined lenders drive Japan's high value and low momentum premiums—also support this argument.

An event study shows that zombies have lower returns than non-zombies after a shock to the banking system. Zombies have a higher bank beta than non-zombies, and zombie losers have particularly high bank beta. When banks have high returns, zombie losers have high returns, driving down momentum for zombies and overall. I find that the best 20 months of bank returns—5.5% of the sample—account for nearly 40% of the difference between zombie momentum and non-zombie momentum.

Event Study I compare cumulative abnormal returns of zombies and non-zombies in November 1997, the beginning of the "acute phase" of Japan's lost two decades and a period associated with tighter credit (Hoshi and Kashyap, 2010). During the month, four financial institutions unexpectedly failed. Like all panics, the panics after the failures in November 1997 were abrupt and unexpected (Nakaso, 2001).

On November 3, Sanyo Securities, a mid-sized brokerage firm with $25 billion in assets, filed for bankruptcy. The event immediately disrupted the domestic interbank market, in which Sanyo Securities was a borrower, and they defaulted on ¥8.3 billion of unsecured funding. Although the amount was small compared to the market's turnover, it was the first loan default in Japan's interbank market history, and this paralyzed the interbank market (Nakaso, 2001). The Japan premium—the spread between the 3-month Eurodollar Tokyo Interbank Borrowing Rate and Libor—spiked. Two weeks later, Japan's tenth largest bank failed, and on November 24, Yamaichi Securities, one of Japan's four major securities dealers, abruptly failed (Nakaso, 2001). On November 26, Tokuyo City Bank failed, and market participants began to speculate about other regional banks' collapse. Many viewed November 26 as the day Japan's financial system was closest to a systemic collapse (Nakaso, 2001). Ultimately, the panic abated after the Finance Minister and the Governor of the Bank of Japan issued a joint statement that reaffirmed their "strong will to fulfill the commitment to ensure the stability of interbank transactions as well as to fully protect deposits."

I study cumulative abnormal returns compared to a CAPM model. I use daily data before November 3, 1997, and regress the return of each firm i on the market return:

$$R_{i,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \varepsilon_{i,t}. \tag{2.11}$$

I use the estimated coefficients to calculate each firm's predicted returns, $\hat{R}_{i,t}$, and I calculate the abnormal return, $AR_{i,t}$, as the difference between the realized and predicted return:

$$AR_{i,t} = R_{i,t} - \hat{R}_{i,t}. \tag{2.12}$$

Figure 2.4 shows the cumulative abnormal returns for zombie and non-zombie firms over November 1997. I sort firms into five equal groups using the interest-rate gap, and I calculate the value-weighted cumulative abnormal return for the zombie and non-zombie groups. After each of the four events, the zombies earned lower cumulative abnormal returns than non-zombies.

Sorting firms based on industry, a related but distinct measure of zombie-ness, generates a similar result. Caballero et al. (2008) find that the manufacturing industry has a lower incidence of zombies than construction, real estate, wholesale and retail, and services industries since manufacturing firms face more global competition than non-manufacturing firms. Thus, a firm's industry is a measure of zombie-ness that does not rely on the balance sheet data used to calculate the interest-rate gap.

Figure 2.5 shows that non-manufacturing firms—which are more likely to be zombies—saw large negative cumulative abnormal returns over November 1997. Meanwhile, manufacturing firms' returns align with market returns.[7] Appendix 2.7.2 shows similar results in Europe. Around negative financial news, European zombies have large negative cumulative abnormal returns relative to non-zombies.

Zombie Bank Beta Zombies have a higher bank beta than non-zombies. Bank distress translates to concern about zombie firms' underlying funding and has a differential effect between zombie and non-zombies returns.

I sort firms into five equal-sized groups based on the interest-rate gap and construct daily value-weighted portfolios. The non-zombie portfolio consists of firms with the largest interest-rate gaps, and firms in the zombie portfolio have the most negative interest-rate gaps. Table 2.7 regresses the portfolio returns on daily

[7] Datastream does not classify firms into similar industry groups as Caballero et al. (2008), so I hand-classify the manufacturing and non-manufacturing groups. The left panel of Figure 2.5 shows value-weighted cumulative abnormal returns for two groups: manufacturing companies and companies in the construction, retailer, and services industries, which leaves some firms unclassified. In the right panel, I classify the remaining firms. I match the group based on which industry descriptor best fits—for example, I place "Media Agencies" into the non-manufacturing group.

bank returns. When banks have weak returns, or weak returns relative to the market, zombies also have lower returns.[8] Appendix 2.7.2 shows similar results in Europe.

Zombie Losers' High Bank Beta Drives Low Momentum There is also a differential bank beta *within* zombies: zombie losers have a higher bank beta than zombie winners. When banks have strong returns, zombie losers have outsized returns, driving down zombie momentum. Non-zombies winners and losers have similar bank beta, so non-zombie momentum is not affected by strong bank returns.

I study the difference between zombie and non-zombie momentum:

$$\begin{aligned} \mathit{MomDiff} &= \text{Zombie Momentum} - \text{Non-zombie Momentum} \\ &= (\text{Zombie Winners} - \text{Zombie Losers}) - (\text{Non-zombie Winners} - \text{Non-zombie Losers}). \end{aligned} \tag{2.13}$$

I classify zombie and non-zombie winners and losers using the same breakpoints (the full data's cutoffs). In this way, the overall momentum series combines value-weighted zombie and non-zombie momentum. Table 2.8 shows the regression of each value-weighted leg on bank returns. Zombie losers have the highest bank beta and have the best performance when banks outperform relative to the market. Table 2.9 shows that zombie losers have the strongest returns on top bank return months, leading zombie momentum to perform poorly and the gap between zombie and non-zombie momentum to widen.

Figure 2.6 shows the cumulative difference between zombie and non-zombie momentum returns and the cumulative difference in the 20 months with the largest bank returns. Figure 2.7 plots the contribution of the 20 months to the overall difference. The results show that the top 20 months, which constitute 5.5% of the sample, contribute over 40% of the difference between zombie momentum and non-zombie momentum.

Momentum and Government Risk The existence of zombies depends on the ability of banks to continue providing subsidized credit. Zombies ultimately rely on the government to continue allowing banks to forbear on zombies' loans. I show that momentum loads on the government risk from Ross (2021).

Adjusting for zombies removes the factor's dependence on the government's constraints. Figure 2.8 shows each momentum factor's beta to the government risk factor from a regression with controls for the market, size, and value factors. Once the momentum factor is adjusted for zombies—either by dropping crisp zombies, dropping crisp and fuzzy zombies, triple-sorting crisp zombies, or triple-sorting crisp and fuzzy zombies—momentum no longer loads on government risk.

[8] I use the Nikkei 225 returns for the market return. For the daily Japanese bank return, I use a value-weighted return of all Japanese stocks in Datastream in the industry "Banks". All daily returns are in log terms.

2.4 Conclusion

I show that the effects of regulatory forbearance confound asset pricing premiums in Japan. After controlling for zombies, value and momentum look more similar to value and momentum internationally. Japanese momentum is very low without controlling for zombies because zombie losers' high bank beta leads to declines in zombie momentum in months with strong bank returns.

Ultimately, zombies are about optimal bank policy when facing crises and lending. In the recovery stage of a crisis, banks must provide credit, and it is critical that the funding supports productive firms rather than insolvent firms that would be unable to survive without subsidized credit. Failing to allocate credit to the appropriate firms has broad implications for both productivity and asset prices.

2.5 Tables

Dataset	Full Data	Drop Crisp Zombies	Drop Crisp + Fuzzy Zombies	Random Half	Random Other Half
VALUE PREMIUM					
Mean	11.45	10.15	8.02	10.87	12.15
(t-statistic)	(4.46)	(3.87)	(2.97)	(3.83)	(4.63)
Standard Deviation	15.24	15.63	16.27	16.89	15.49
Sharpe Ratio	0.75	0.65	0.49	0.64	0.78
VALUE STRATEGY					
Mean	9.57	9.09	7.76	9.37	9.31
(t-statistic)	(4.17)	(3.63)	(2.97)	(4.09)	(3.72)
Standard Deviation	13.74	15.00	15.74	13.71	14.97
Sharpe Ratio	0.70	0.61	0.49	0.68	0.62
MOMENTUM PREMIUM					
Mean	0.96	2.73	2.82	0.42	1.99
(t-statistic)	(0.31)	(0.84)	(0.86)	(0.12)	(0.65)
Standard Deviation	19.17	19.94	20.29	21.08	18.78
Sharpe Ratio	0.05	0.14	0.14	0.02	0.11
MOMENTUM STRATEGY					
Mean	0.93	1.81	2.94	0.66	1.16
(t-statistic)	(0.35)	(0.66)	(1.04)	(0.24)	(0.42)
Standard Deviation	16.66	17.08	17.31	16.92	17.28
Sharpe Ratio	0.06	0.11	0.17	0.04	0.07

Table 2.1: Value and Momentum in Japan. Table presents the average return, t-statistic of the average return, the standard deviation of returns, and the Sharpe ratio for the value premium, value strategy, momentum premium, and momentum strategy factors. Statistics are computed from monthly returns and reported as annualized numbers. See the text for details on the factors' construction.

	Mean				Sharpe Ratio			
	Value Premium	Momentum Premium	Value Strategy	Momentum Strategy	Value Premium	Momentum Premium	Value Strategy	Momentum Strategy
International								
U.S.	1.16	3.71	2.37	5.89	0.10	0.25	0.16	0.36
Europe	3.07	5.50	2.84	7.43	0.28	0.38	0.28	0.56
U.K.	3.73	8.20	4.02	9.65	0.28	0.51	0.29	0.61
Global Average	2.66	5.80	3.08	7.66	0.22	0.38	0.24	0.51
Global Factor			4.21	6.14			0.39	0.50
Japan								
Full Data	10.96	0.64	9.66	0.59	0.59	0.05	0.63	0.10
Drop Crisp Zombies	9.59	2.50	9.16	1.51	0.60	0.12	0.60	0.09
Drop Crisp and Fuzzy Zombies	7.36	2.60	7.75	2.69	0.45	0.13	0.48	0.15
Japan vs. International								
Ratio (relative to Global Average)								
Full Data	4.13×	0.11×	3.14×	0.08×	2.67×	0.14×	2.61×	0.20×
Drop Crisp Zombies	3.61×	0.43×	2.98×	0.20×	2.74×	0.33×	2.49×	0.17×
Drop Crisp and Fuzzy Zombies	2.77×	0.45×	2.52×	0.35×	2.02×	0.33×	2.01×	0.30×
Ratio (relative to Global Factor)								
Full Data			2.29×	0.10×			1.61×	0.20×
Drop Crisp Zombies			2.17×	0.25×			1.53×	0.18×
Drop Crisp and Fuzzy Zombies			1.84×	0.44×			1.23×	0.31×

Table 2.2: Global Comparison of Value and Momentum. Table presents the average return in percent and the Sharpe ratio for the value premium, value strategy, momentum premium, and momentum strategy factors internationally. Japan's factors are calculated with crisp zombies removed and crisp and fuzzy zombies removed. International data are from the AQR website, including the Global Average (calculated as the equal-weighted average of the U.S., the U.K., and Europe premiums or strategies) and the Global Strategy Factor. Ratios are calculated as the Japan statistics divided by the Global Average or the Global Factor. Statistics are computed from monthly returns and reported as annualized numbers. See the text for details on the factors' construction.

Dataset	Full Data	Firms with Only Japanese Lead Arrangers	Firms with International Lead Arrangers	Firms with Capital Injection Lead Arrangers	Firms without Capital Injection Lead Arrangers
VALUE PREMIUM					
Mean	6.61	16.84	6.37	14.20	3.30
(t-statistic)	(1.78)	(3.66)	(1.57)	(3.44)	(0.79)
Standard Deviation	15.89	18.92	17.36	17.15	18.13
Sharpe Ratio	0.42	0.89	0.37	0.83	0.18
MOMENTUM PREMIUM					
Mean	0.79	−4.68	4.30	−1.35	3.98
(t-statistic)	(0.20)	(−1.01)	(0.95)	(−0.34)	(0.95)
Standard Deviation	17.29	21.01	19.62	17.92	18.15
Sharpe Ratio	0.05	−0.22	0.22	−0.08	0.22

Table 2.3: Value and Momentum for Japanese Firms Classified by Syndicated Loan Lending Relationships. Table presents the average return in percent, t-statistic of the average return, the standard deviation of returns, and the Sharpe ratio for the value premium, value strategy, momentum premium, and momentum strategy factors. Statistics are calculated separately for firms in the full liquid sample from Asness et al. (2013a), for firms with only Japanese lead arrangers, firms with international lead arrangers, firms with capital injection lead arrangers, and firms without capital injection lead arrangers. Statistics are computed from monthly returns and reported as annualized numbers. See the text for details on the samples and factors' construction.

Prices of Risk: $\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f$	Unadjusted Factors			Drop Crisp		Drop Crisp + Fuzzy		Triple-Sort Crisp		Triple-Sort Crisp + Fuzzy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	0.205	−0.397	−0.093	−0.533	0.125	−0.628	0.050	−0.534	−0.110	−0.536	−0.041
	(0.27)	(−0.64)	(−0.15)	(−0.80)	(0.20)	(−0.91)	(0.08)	(−0.81)	(−0.17)	(−0.81)	(−0.06)
	(0.27)	(−0.61)	(−0.14)	(−0.77)	(0.17)	(−0.87)	(0.06)	(−0.77)	(−0.15)	(−0.77)	(−0.06)
$Mkt - R_f$	−0.012	0.461	0.181	0.592	−0.012	0.688	0.067	0.591	0.196	0.592	0.132
	(−0.01)	(0.67)	(0.26)	(0.81)	(−0.02)	(0.92)	(0.09)	(0.82)	(0.27)	(0.82)	(0.19)
	(−0.01)	(0.64)	(0.25)	(0.79)	(−0.01)	(0.88)	(0.08)	(0.79)	(0.25)	(0.78)	(0.17)
SMB		0.185	0.186	0.176	0.182	0.175	0.179	0.180	0.194	0.178	0.191
		(1.02)	(1.03)	(0.97)	(1.00)	(0.97)	(0.99)	(1.00)	(1.07)	(0.98)	(1.05)
		(1.02)	(1.02)	(0.97)	(0.99)	(0.97)	(0.97)	(1.00)	(1.06)	(0.98)	(1.04)
HML		0.309	0.318								
		(1.87)	(1.93)								
		(1.85)	(1.91)								
WML			0.774								
			(1.26)								
			(1.17)								
HML_{ZA}				0.628	−0.245	0.703	−0.214	0.554	−0.046	0.560	−0.085
				(1.81)	(−0.67)	(1.82)	(−0.54)	(1.95)	(−0.14)	(1.92)	(−0.26)
				(1.75)	(−0.65)	(1.75)	(−0.50)	(1.88)	(−0.13)	(1.85)	(−0.24)
WML_{ZA}					1.689		1.882		1.217		1.345
					(2.58)		(2.71)		(1.76)		(1.98)
					(2.33)		(2.38)		(1.59)		(1.78)
Ann. Risk Premium ($\sigma^\beta \times \lambda$)			0.43		2.32		2.16		1.73		1.86
TS GRS p-value	0.12	0.16	0.20	0.10	0.07	0.17	0.31	0.08	0.02	0.10	0.05
MAPE (%)	0.16	0.11	0.11	0.12	0.12	0.12	0.10	0.13	0.15	0.13	0.14
TS Avg R^2	0.77	0.92	0.93	0.91	0.92	0.91	0.92	0.92	0.92	0.92	0.92
Quarters (T)	332	332	332	332	332	332	332	332	332	332	332
Portfolios (N)	25	25	25	25	25	25	25	25	25	25	25

Table 2.4: Cross-Sectional Regressions with Zombie-Adjusted Factors. Table presents the cross-sectional pricing results for the 25 Fama–French monthly portfolios, which are double-sorted on size and book-to-market. The regressions test if the portfolios are priced by the Japanese Fama–French factors and zombie-adjusted factors, which are adjusted by dropping crisp zombies, dropping crisp and fuzzy zombies, triple-sorting crisp zombies, and triple-sorting crisp and fuzzy zombies. See the text for additional details on the factors. Coefficients are the price of risk estimates, and Fama–MacBeth and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium ($\sigma^\beta \times \lambda$) is the annualized increase in expected risk premium associated with a one standard deviation increase in the portfolio's beta to the momentum factor. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2.

Panel A: Fama–French Factors					
	Intercept	$Mkt - R_f$	SMB	HML	WML
$Mkt - R_f$	0.251		0.173	−0.453	−0.280
	(0.86)		(1.91)	(−4.36)	(−4.11)
SMB	0.099	0.064		0.119	−0.039
	(0.56)	(1.91)		(1.84)	(−0.91)
HML	0.335	−0.121	0.086		−0.200
	(2.24)	(−4.36)	(1.84)		(−5.81)
WML	0.281	−0.175	−0.065	−0.466	
	(1.23)	(−4.11)	(−0.91)	(−5.81)	
Panel B: Zombie-Adjusted Factors, Drop Crisp Zombies					
	Intercept	$Mkt - R_f$	SMB	HML_{ZA}	WML_{ZA}
$Mkt - R_f$	0.446		0.146	−0.408	−0.354
	(1.48)		(1.61)	(−4.47)	(−4.15)
SMB	0.157	0.054		−0.015	−0.050
	(0.85)	(1.61)		(−0.26)	(−0.94)
HML_{ZA}	0.847	−0.141	−0.014		−0.661
	(4.93)	(−4.47)	(−0.26)		(−18.30)
WML_{ZA}	0.797	−0.141	−0.054	−0.764	
	(4.28)	(−4.15)	(−0.94)	(−18.30)	
Panel C: Zombie-Adjusted Factors, Drop Crisp and Fuzzy Zombies					
	Intercept	$Mkt - R_f$	SMB	HML_{ZA}	WML_{ZA}
$Mkt - R_f$	0.370		0.152	−0.376	−0.317
	(1.24)		(1.68)	(−4.55)	(−3.88)
SMB	0.148	0.056		−0.005	−0.039
	(0.82)	(1.68)		(−0.10)	(−0.77)
HML_{ZA}	0.730	−0.157	−0.006		−0.684
	(3.86)	(−4.55)	(−0.10)		(−17.65)
WML_{ZA}	0.695	−0.138	−0.046	−0.712	
	(3.59)	(−3.88)	(−0.77)	(−17.65)	
Panel D: Zombie-Adjusted Factors, Triple-Sort Crisp Zombies					
	Intercept	$Mkt - R_f$	SMB	HML_{ZA}	WML_{ZA}
$Mkt - R_f$	0.502		0.169	−0.504	−0.427
	(1.69)		(1.89)	(−5.30)	(−5.11)
SMB	0.082	0.064		0.071	−0.015
	(0.45)	(1.89)		(1.17)	(−0.29)
HML_{ZA}	0.814	−0.156	0.058		−0.578
	(5.09)	(−0.53)	(1.17)		(−15.87)
WML_{ZA}	0.693	−0.173	−0.016	−0.752	
	(3.73)	(−5.11)	(−0.29)	(−15.87)	
Panel E: Zombie-Adjusted Factors, Triple-Sort Crisp and Fuzzy Zombies					
	Intercept	$Mkt - R_f$	SMB	HML_{ZA}	WML_{ZA}
$Mkt - R_f$	0.484		0.163	−0.501	−0.417
	(1.63)		(1.82)	(−5.33)	(−5.01)
SMB	0.102	0.062		0.052	−0.024
	(0.56)	(1.82)		(0.86)	(−0.45)
HML_{ZA}	0.773	−0.159	0.043		−0.587
	(4.77)	(−5.33)	(0.86)		(−16.21)
WML_{ZA}	0.691	−0.171	−0.026	−0.757	
	(3.71)	(−5.01)	(−0.45)	(−16.21)	

Table 2.5: Spanning Tests for Zombie-Adjusted Factors. Table presents time-series regressions at the monthly level. The regressions test if each factor is spanned by other factors. Panel A uses the Fama–French factors. Panels B, C, D, and E use the zombie-adjusted factors HML_{ZA} and WML_{ZA}, created by dropping crisp zombies, dropping crisp and fuzzy zombies, triple-sorting crisp zombies, and triple-sorting crisp and fuzzy zombies. t-statistics using robust standard errors are reported in parentheses.

Panel A: Fama–French Factors					
	Intercept		Intercept		Intercept
$Mkt - R_f$	0.416	$Mkt - R_f$	0.574	$Mkt - R_f$	0.252
	(1.49)		(2.43)		(0.86)
SMB	0.148	SMB	0.245	SMB	0.027
	(0.83)		(1.39)		(0.16)
HML	0.405	HML	0.451	HML	0.337
	(2.92)		(2.87)		(2.25)
WML	0.194	WML	0.196	WML	0.171
	(0.85)		(0.82)		(0.77)
RMW	0.225	QMJ	0.376	BAB	0.280
	(2.24)		(2.90)		(1.32)

Panel B: Zombie-Adjusted Factors, Drop Crisp Zombies					
	Intercept		Intercept		Intercept
$Mkt - R_f$	0.687	$Mkt - R_f$	0.745	$Mkt - R_f$	0.478
	(2.38)		(3.14)		(1.58)
SMB	0.253	SMB	0.309	SMB	0.061
	(1.38)		(1.70)		(0.34)
HML_{ZA}	0.918	HML_{ZA}	0.932	HML_{ZA}	0.873
	(5.76)		(5.18)		(5.11)
WML_{ZA}	0.844	WML_{ZA}	0.823	WML_{ZA}	0.766
	(4.49)		(4.10)		(4.09)
RMW	0.321	QMJ	0.474	BAB	0.392
	(3.09)		(3.53)		(1.76)

Panel C: Zombie-Adjusted Factors, Drop Crisp and Fuzzy Zombies					
	Intercept		Intercept		Intercept
$Mkt - R_f$	0.556	$Mkt - R_f$	0.615	$Mkt - R_f$	0.393
	(1.95)		(2.62)		(1.31)
SMB	0.222	SMB	0.277	SMB	0.071
	(1.23)		(1.56)		(0.40)
HML_{ZA}	0.797	HML_{ZA}	0.741	HML_{ZA}	0.746
	(4.48)		(3.69)		(3.94)
WML_{ZA}	0.717	WML_{ZA}	0.671	WML_{ZA}	0.655
	(3.68)		(3.20)		(3.38)
RMW	0.257	QMJ	0.396	BAB	0.315
	(2.47)		(2.93)		(1.42)

Panel D: Zombie-Adjusted Factors, Triple-Sort Crisp Zombies					
	Intercept		Intercept		Intercept
$Mkt - R_f$	0.749	$Mkt - R_f$	0.793	$Mkt - R_f$	0.524
	(2.64)		(3.36)		(1.76)
SMB	0.166	SMB	0.230	SMB	−0.012
	(0.90)		(1.27)		(−0.07)
HML_{ZA}	0.889	HML_{ZA}	0.892	HML_{ZA}	0.834
	(5.97)		(5.29)		(5.21)
WML_{ZA}	0.735	WML_{ZA}	0.671	WML_{ZA}	0.627
	(3.91)		(3.32)		(3.38)
RMW	0.343	QMJ	0.483	BAB	0.382
	(3.26)		(3.61)		(1.73)

Panel E: Zombie-Adjusted Factors, Triple-Sort Crisp and Fuzzy Zombies					
	Intercept		Intercept		Intercept
$Mkt - R_f$	0.730	$Mkt - R_f$	0.751	$Mkt - R_f$	0.508
	(2.59)		(3.20)		(1.71)
SMB	0.188	SMB	0.244	SMB	0.010
	(1.03)		(1.35)		(0.06)
HML_{ZA}	0.848	HML_{ZA}	0.824	HML_{ZA}	0.794
	(5.67)		(4.82)		(4.90)
WML_{ZA}	0.736	WML_{ZA}	0.653	WML_{ZA}	0.636
	(3.91)		(3.22)		(3.41)
RMW	0.332	QMJ	0.462	BAB	0.373
	(3.20)		(3.46)		(1.69)

Table 2.6: Spanning Tests with Quality Factors. Table presents the intercepts and t-statistics from monthly time-series regressions of each factor on the other four factors in the column. For example, the first coefficient is the intercept from the regression of the market factor on SMB, HML, WML, and RMW. The last coefficient is the intercept from the regression of BAB on the market factor, SMB, HML_{ZA}, and WML_{ZA}, where HML_{ZA} and WML_{ZA} are constructed by triple-sorting crisp and fuzzy zombies.

	Zombie	Non-zombie	Zombie−Non-zombie	Zombie−Non-zombie		
				Full Sample	Pre-crisis	Post-crisis
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Return	0.551***	0.526***	0.060**			
	(17.16)	(15.71)	(2.98)			
Bank Return−Market Return				0.068**	0.151*	0.046**
				(3.33)	(3.15)	(2.88)
N	8,958	8,392	8,392	7,854	2,623	4,505
Adj. R^2	0.38	0.36	0.01	0.00	0.01	0.00
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.7: Bank Betas in Japan. Table presents time-series regressions at the daily level. The dependent variable is the value-weighted portfolio return. Firms are sorted into five equal-sized groups based on the interest-rate gap; the zombie portfolio consists of firms with the most negative interest-rate gap, and the non-zombie portfolio consists of firms with the largest interest-rate gap. Independent variables are the domestic bank return, alone and relative to the market return. Intercept is included in each regression but omitted from the table. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel A: Bank Beta

	Non-zombie Winners		Non-zombie Losers		Zombie Winners		Zombie Losers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank Return	0.528^{***}	0.501^{***}	0.624^{***}	0.614^{***}	0.584^{***}	0.557^{***}	0.683^{***}	0.675^{***}
	(9.26)	(7.45)	(9.62)	(8.89)	(8.30)	(7.31)	(10.70)	(9.73)
N	374	374	374	374	374	374	373	373
Adj. R^2	0.33	0.36	0.45	0.45	0.39	0.42	0.47	0.47
Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Market Beta

	Non-zombie Winners		Non-zombie Losers		Zombie Winners		Zombie Losers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market Return	0.574^{***}	0.527^{***}	0.691^{***}	0.681^{***}	0.582^{***}	0.539^{***}	0.672^{***}	0.654^{***}
	(7.76)	(6.70)	(8.97)	(8.24)	(7.25)	(6.45)	(8.76)	(7.69)
N	374	374	374	374	374	374	373	373
Adj. R^2	0.22	0.24	0.31	0.29	0.22	0.24	0.26	0.23
Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel C: Bank Beta, Controlling for Market Beta

	Non-zombie Winners		Non-zombie Losers		Zombie Winners		Zombie Losers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank Return−Market Return	0.233^{***}	0.242^{**}	0.267^{***}	0.276^{***}	0.292^{***}	0.296^{***}	0.349^{***}	0.360^{***}
	(3.68)	(3.62)	(4.32)	(4.19)	(4.77)	(4.59)	(5.44)	(5.30)
N	374	374	374	374	374	374	373	373
Adj. R^2	0.05	0.13	0.07	0.09	0.08	0.15	0.11	0.13
Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 2.8: Bank Beta and Market Beta for Momentum Legs. Table presents time-series regressions at the monthly level. The dependent variable is the value-weighted portfolio return. Independent variables are the bank return, the market return, and the difference between the bank return and market return. Intercept is included in each regression but omitted from the table. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel A: Returns in Top Bank Return Months

	Zombie−Non-zombie Momentum	Zombie Momentum	Non-zombie Momentum	Zombie Winners	Zombie Losers	Non-zombie Winners	Non-zombie Losers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝕀(Top Bank Return)	-0.024^{*}	-0.056^{***}	-0.032^{*}	0.082^{***}	0.131^{***}	0.078^{***}	0.108^{***}
	(−2.16)	(−3.88)	(−2.25)	(5.53)	(8.93)	(5.27)	(8.93)
N	360	360	360	360	360	360	360
Adj. R^2	0.01	0.05	0.01	0.08	0.18	0.07	0.14

Panel B: Returns in Top Market Return Months

	Zombie−Non-zombie Momentum	Zombie Momentum	Non-zombie Momentum	Zombie Winners	Zombie Losers	Non-zombie Winners	Non-zombie Losers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝕀(Top Market Return)	−0.012	−0.028	−0.016	0.057^{***}	0.082^{***}	0.050^{***}	0.066^{***}
	(−0.93)	(−1.75)	(−1.35)	(4.07)	(4.93)	(3.63)	(4.60)
N	360	360	360	360	360	360	360
Adj. R^2	0.00	0.01	0.00	0.04	0.07	0.03	0.05

Panel C: Returns in Top Bank Return Months and Top Market Return Months

	Zombie−Non-zombie Momentum	Zombie Momentum	Non-zombie Momentum	Zombie Winners	Zombie Losers	Non-zombie Winners	Non-zombie Losers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝕀(Top Bank Return)	-0.022^{*}	-0.053^{***}	-0.031^{*}	0.076^{***}	0.123^{***}	0.074^{***}	0.102^{***}
	(−1.98)	(−3.54)	(−2.10)	(5.29)	(8.27)	(5.03)	(8.73)
𝕀(Top Market Return)	−0.010	−0.022	−0.012	0.049^{***}	0.068^{***}	0.042^{***}	0.054^{***}
	(−0.71)	(−1.33)	(−1.03)	(3.84)	(4.47)	(3.37)	(4.51)
N	360	360	360	360	360	360	360
Adj. R^2	0.01	0.06	0.01	0.11	0.23	0.09	0.17

Table 2.9: Returns in Months with Top Bank and Market Performance. Table presents time-series regressions at the monthly level. The dependent variable is the value-weighted portfolio return. Zombie momentum is the zombie winners portfolio minus the zombie losers portfolio. Non-zombie momentum is the non-zombie winners portfolio minus the non-zombie losers portfolio. Independent variables are indicators for the top bank return months and top market return months. 𝕀(Top Bank Return) = 1 if the month is a top 20 bank return month, and 0 otherwise. 𝕀(Top Market Return) = 1 if the month is a top 20 market return month, and 0 otherwise. Intercept is included in each regression but omitted from the table. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.6 Figures

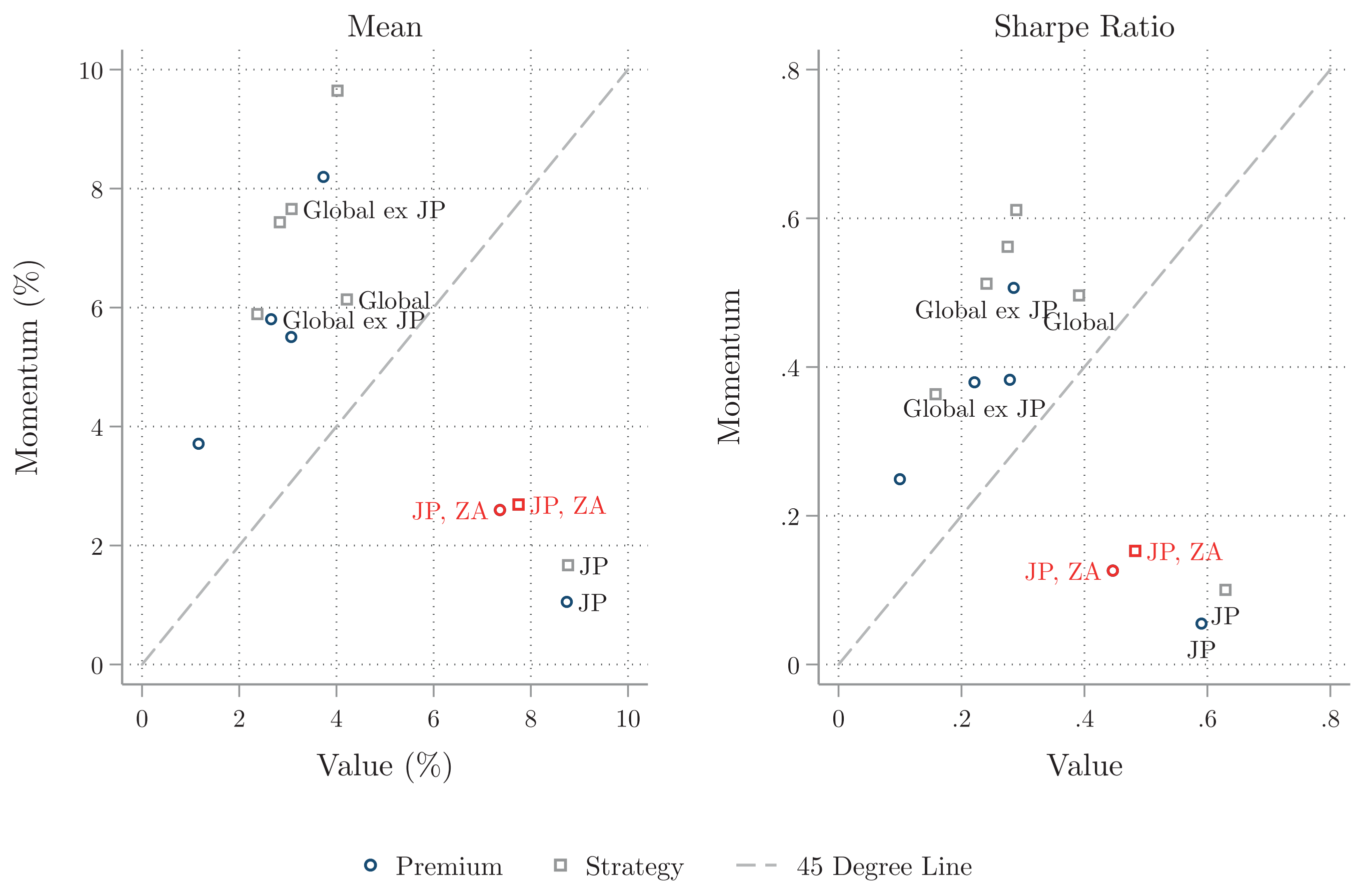


Figure 2.1: Global Comparison of Value and Momentum. Figure shows the average returns and Sharpe ratios for value and momentum premiums and strategies in the U.S., Europe, U.K., and Japan. See the text for details on the factors' construction. Left panel plots the average returns, and right panel plots the Sharpe ratio. International statistics are calculated using data from the AQR website. Statistics are computed from monthly returns and reported as annualized numbers.

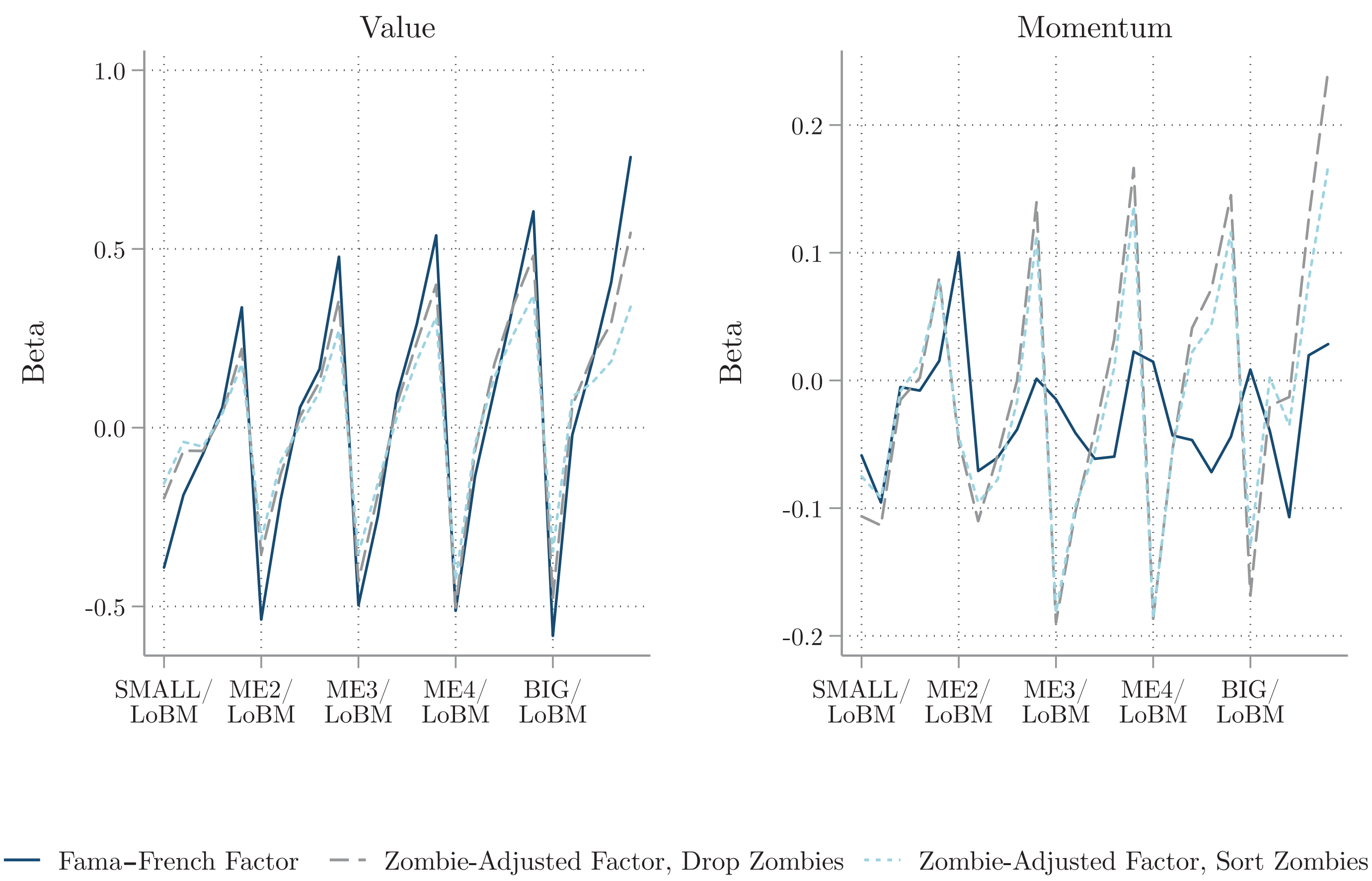


Figure 2.2: Value and Momentum Betas. Figure shows the betas of the 25 Fama–French portfolios to value and momentum factors. Betas are estimated using the four-factor model. Left panel plots betas to the value factors, HML and HML_{ZA}. Right panel plots betas to the momentum factors, WML and WML_{ZA}. Zombie-adjusted factors, HML_{ZA} and WML_{ZA}, are constructed by dropping zombies and triple-sorting zombies. Section 3.4 for details on the construction of the zombie-adjusted factors.

Figure 2.3: Securities Market Line for Value and Momentum. Figure shows the betas of the 25 Fama–French portfolios to value and momentum factors and the portfolios' expected returns. Betas are estimated using the four-factor model. Top panel plots betas to the value factors, HML and HML_{ZA}. Bottom panel plots betas to the momentum factors, WML and WML_{ZA}. Zombie-adjusted factors, HML_{ZA} and WML_{ZA}, are constructed by dropping zombies and triple-sorting zombies. Section 3.4 for details on the construction of the zombie-adjusted factors.

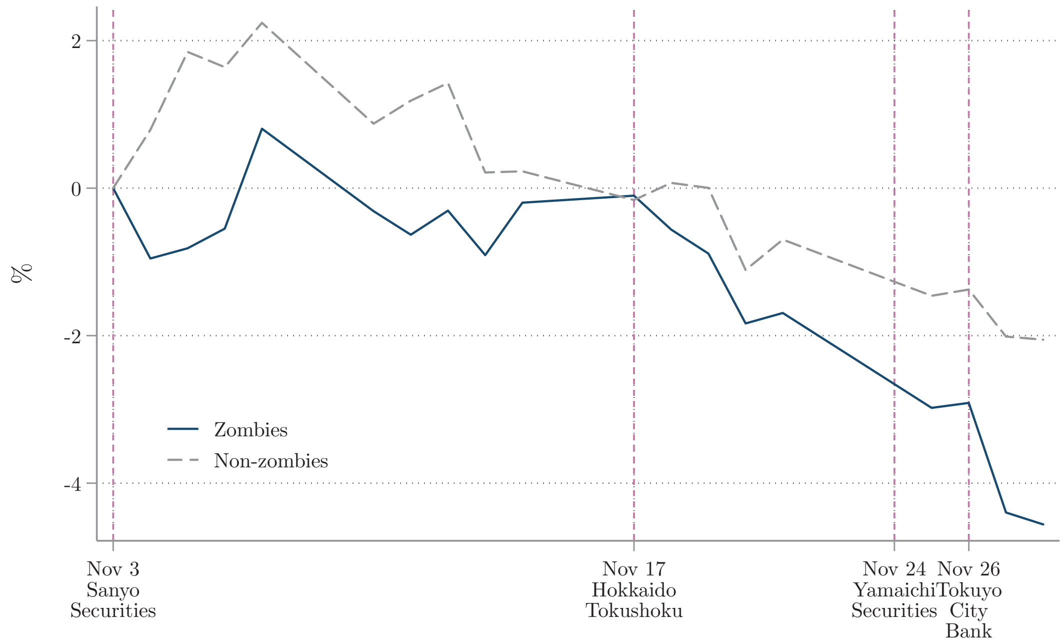


Figure 2.4: Cumulative Abnormal Returns in Japan, November 1997. Figure shows the daily value-weighted cumulative abnormal returns for zombies and non-zombies. Each firm's abnormal returns are calculated as the difference between the realized return and predicted return, which is estimated using the CAPM beta before November 3, 1997, the day of the Sanyo Securities' failure. Vertical lines mark the dates of the four bank failures.

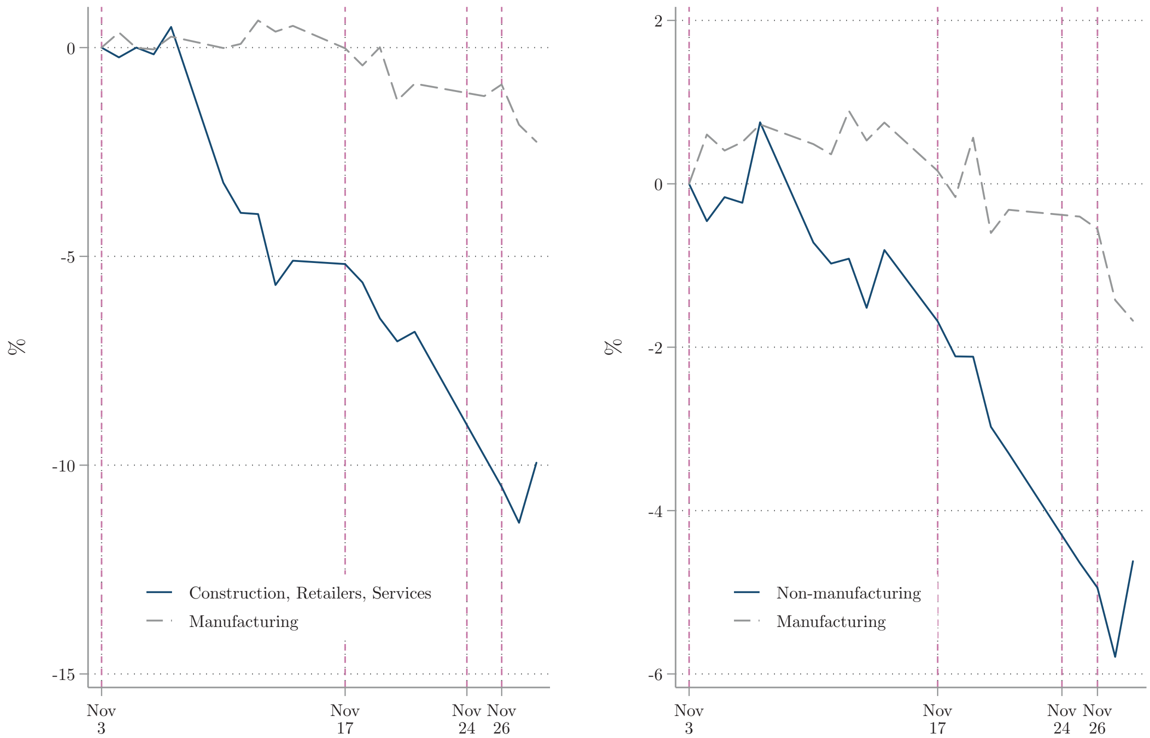


Figure 2.5: Cumulative Abnormal Returns in Japan, November 1997. Figure shows the daily value-weighted cumulative abnormal returns manufacturing and non-manufacturing firms. Left panel considers construction companies, retailers, and services firms as non-manufacturing. Right panel includes other non-manufacturing industries. Each firm's abnormal returns are calculated as the difference between the realized return and predicted return, which is estimated using the CAPM beta before November 3, 1997, the day of the Sanyo Securities' failure. Vertical lines mark the dates of the four bank failures.

Figure 2.6: Cumulative Difference in Zombie and Non-zombie Momentum

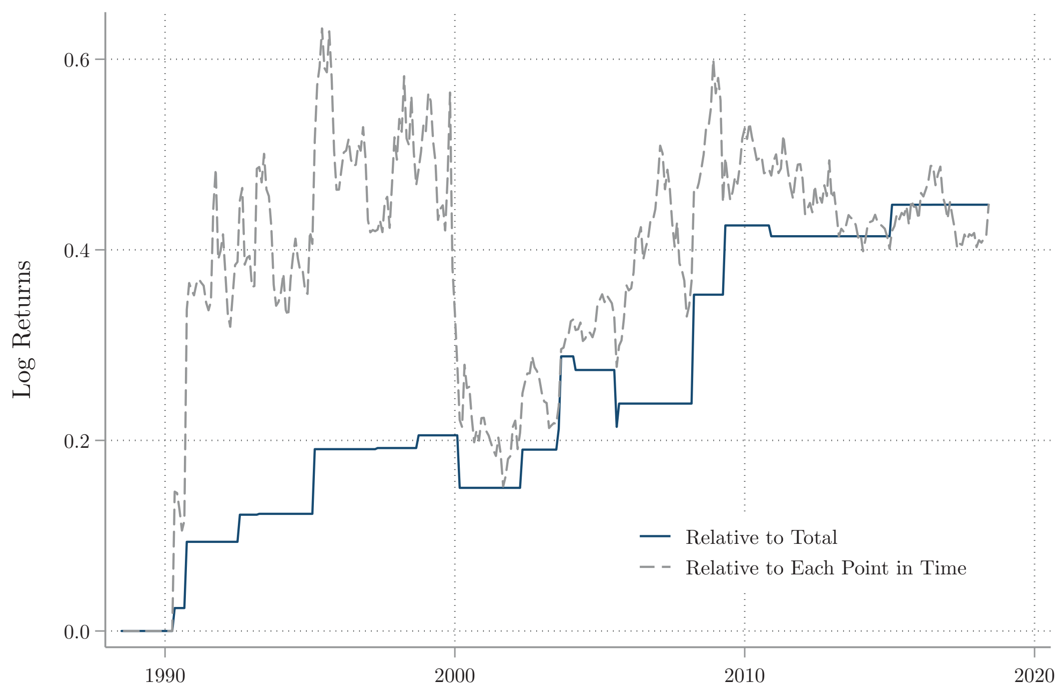


Figure 2.7: Contribution of Top 20 Bank Return Months, Relative to Cumulative Difference

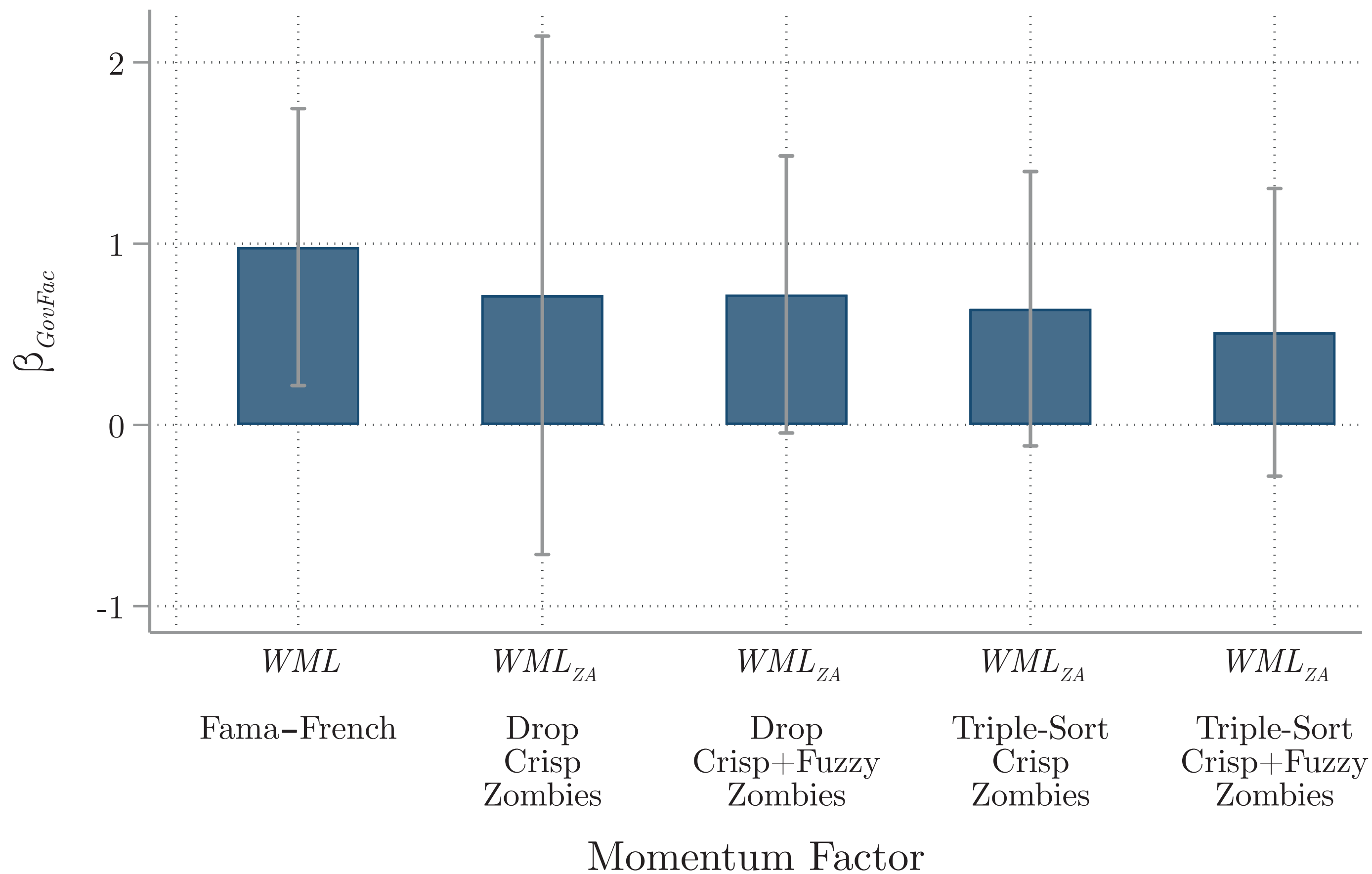


Figure 2.8: Momentum Factors' Betas to Government Risk. Figure shows the betas of Japanese momentum factors to the Japanese government risk factor. Betas are estimated controlling for the excess market return, *SMB*, and *HML*. The momentum factors used include the Fama–French factor *WML* and four zombie-adjusted factors WML_{ZA}. Zombie-adjusted factors are constructed by dropping crisp zombies, dropping crisp and fuzzy zombies, triple-sorting crisp zombies, or triple-sorting crisp and fuzzy zombies. See Section 3.4 for details on the construction of the zombie-adjusted factors.

2.7 Appendix

2.7.1 Value and Momentum Details

Value and Momentum Summary Statistics Combined, crisp and fuzzy zombies make up 50% to 60% of firms in the high and low value and momentum terciles (Table 2.10). There are more zombies in high value stocks and past loser stocks. Table 2.11 shows the returns of each leg of the value and momentum premiums. Dropping zombies increases the returns of both winners and losers, but the improvement is smaller for losers. Value (P3) exceeds growth (P1) in all three datasets, and the the value premium decreases with zombies removed because the growth tercile return increases while the value tercile remains more stable.

Dropping zombies does not change the strong negative correlation between value and momentum. Table 2.12 shows that value and momentum premiums have a correlation coefficient of −0.62 for the premiums and −0.65 for the strategies, compared to −0.60 and −0.66 with zombies included.

2.7.2 European Zombies

Event Study Since the Global Financial Crisis, zombies have been on the rise in Europe. I identify European zombies following the method described in Section 3.4. Since the short-term and long-term prime rates are not available, I use the European Central Bank rate on the marginal lending facility, which offers overnight credit to banks.

Similar to Japan in 1997, European event studies show that bad news for banks leads to lower abnormal returns for firms receiving subsidized credit from banks compared to non-zombies. Upon the announcement of additional government support, zombies have positive abnormal returns relative to non-zombies. Three early Global Financial Crisis events in Europe illustrate the divergence in abnormal returns.

On August 9, 2007, BNP Paribas—France's largest bank, the Eurozone's second-largest bank by market value, and the world's third-largest bank by assets—froze three mortgage-related investment funds that totaled €1.6 billion ($2.2 billion). BNP's suspension of redemptions sparked credit concerns both in Europe and worldwide as the TED and LIBOR-OIS spreads saw sharp upward moves, and many viewed the event as the start of the Global Financial Crisis reaching European markets. Figure 2.9 shows the cumulative abnormal returns for zombies and non-zombies after the event. Zombies suffered lower abnormal returns.

On September 14, 2007, the British bank Northern Rock faced an old-fashioned bank run with depositors lining the streets outside of retail branches. The event was the first run on a British bank in 140 years (since Overend & Gurney in 1866) and occurred despite the Bank of England's announcement the previous day that it would intervene and provide emergency support as the lender of last resort. Depositors withdrew an estimated one billion pounds or around 4% of retail deposits (Slater, 2007). At that time, just 31,700 pounds per person were guaranteed by deposit insurance: more specifically, the first 2000 pounds were fully insured, and then 90% up to 35,000 pounds. On September 17, the U.K. government announced that it would guarantee all deposits at Northern Rock and would provide guarantees for other banks that faced difficulties. This intervention stemmed the bank run, and later, deposit insurance was raised. Figure 2.9 shows the cumulative abnormal returns around the Northern Rock events. Zombies had negative abnormal returns immediately after the bank run; but after the September 17 announcement of government support, zombies had strong positive abnormal returns while non-zombie returns fluctated more closely with market returns.

In September 2008, global sentiment about the financial system was extremely low as funding liquidity dried up following the collapse of Lehman Brothers on September 15, and the LIBOR-OIS spread spiked to over 300 bps. On September 28, Fortis, Belgium's largest bank, was partially nationalized, and the next day, on September 29, zombie cumulative abnormal returns in Europe dropped even lower as Congress failed to pass the U.S. Emergency Economic Stabilization Act of 2008 TARP bill to inject $700 billion of capital injections. Zombies faced strong negative abnormal returns after the event. Markets continued to view the financial system as fragile, and the LIBOR-OIS remained elevated.

On October 8, the British government announced a £500 billion bank rescue package, and the Federal Reserve, European Central Bank, Bank of England, Bank of Canada, Swedish Riksbank, and Swiss National Bank cut rates. On October 10, the U.S. government announced equity purchases of banks as part of the Emergency Economic Stabilization Act. After the large government interventions, zombie cumulative abnormal returns appeared to recover.

Bank Betas In Japan, zombies have higher bank beta than non-zombies, even controlling for the market return. The comparison also holds in Europe, and the result is driven by the post-crisis period after markets are more sensitive to the link between zombies and their underlying funding.

Similar to the method for the Japanese event study, I sort European firms into five equal-sized groups based on the interest-rate gap and construct daily value-weighted portfolios. The non-zombie portfolio consists of firms with the largest interest-rate gap, and the zombie portfolio holds the firms with the most negative interest-rate gap.

Table 2.13 shows that the European zombie portfolio has higher bank beta than the non-zombie portfolio. And when banks outperform the market, zombies outperform non-zombies, which is driven by the post-crisis period. In Table 2.14, I regress daily individual stock returns on bank returns relative to the market return. After the first crisis events for Japan and Europe, zombies have higher beta to bank outperformance than non-zombies.

2.7.3 Appendix Tables

Value	Total	Crisp	Fuzzy
P1	54	44	10
P2	61	49	12
P3	63	52	11

Momentum	Total	Crisp	Fuzzy
P1	63	51	12
P2	61	50	11
P3	55	44	11

Table 2.10: Average Percentage of Zombies. Table shows the average percent of zombies in each tercile of the value and momentum sorts. P1 refers to the lowest tercile, and P3 is the highest tercile.

	P1 (Growth)	P3 (Value)	Value Premium
Full Data	0.03	11.49	11.45
Drop Crisp Zombies	1.40	11.67	10.15
Drop Crisp and Fuzzy Zombies	2.90	11.13	8.02

	P1 (Losers)	P3 (Winners)	Momentum Premium
Full Data	4.87	5.87	0.96
Drop Crisp Zombies	4.62	7.46	2.73
Drop Crisp and Fuzzy Zombies	5.06	8.01	2.82

Table 2.11: Components of Value and Momentum Premiums. Table shows value-weighted portfolio returns. P1 refers to the lowest tercile, and P3 is the highest tercile.

	Premium	Strategy
Full Data (VME)	−0.60	−0.66
Full Data	−0.59	−0.65
Drop Crisp Zombies	−0.62	−0.66
Drop Crisp and Fuzzy Zombies	−0.62	−0.65

Table 2.12: Value and Momentum Correlation. Table shows the correlation between value and momentum premiums and strategies. The value and momentum premiums and strategies are constructed using the full data, dropping crisp zombies, and dropping crisp and fuzzy zombies. The first line of the table uses the updated premium and strategy factors from Asness et al. (2013a) that are available on the AQR website.

	Zombie	Non-zombie	Zombie−Non-zombie	Zombie−Non-zombie		
				Full Sample	Pre-crisis	Post-crisis
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Return	0.778***	0.534***	0.244***			
	(36.78)	(19.54)	(15.82)			
Bank Return−Market Return				0.343***	−0.084	0.482***
				(5.69)	(−0.94)	(12.61)
N	4,804	4,804	4,804	4,726	1,647	2,054
Adj. R^2	0.89	0.63	0.38	0.18	0.00	0.54
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.13: Bank Betas in Europe. Table presents time-series regressions at the daily level. The dependent variable is the value-weighted portfolio return. Firms are sorted into five equal-sized groups based on the interest-rate gap; the zombie portfolio consists of firms with the most negative interest-rate gap, and the non-zombie portfolio consists of firms with the largest interest-rate gap. Independent variables are the domestic bank return, alone and relative to the market return. Intercept is included in each regression but omitted from the table. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Crisis Event	Europe BNP		Japan Sanyo	
	(1) Return	(2) Return	(3) Return	(4) Return
Bank Return−Market Return	0.093	0.094	-0.304^{**}	-0.305^{**}
	(1.51)	(1.51)	(−3.39)	(−3.43)
(Bank Return−Market Return)×$\mathbb{I}$(Zombie)	-0.063^{*}	-0.0621^{*}	-0.253^{**}	-0.251^{**}
	(−2.19)	(−2.12)	(−2.86)	(−2.86)
(Bank Return−Market Return)×$\mathbb{I}$(Post)	0.219^{*}	0.216^{*}	0.276^{**}	0.277^{**}
	(2.79)	(2.73)	(2.78)	(2.80)
(Bank Return−Market Return)×$\mathbb{I}$(Zombie) × $\mathbb{I}$(Post)	0.210^{**}	0.206^{*}	0.263^{**}	0.261^{**}
	(3.01)	(2.85)	(2.88)	(2.89)
Constant	−0.000	0.001^{***}	0.000	-0.000^{***}
	(−0.09)	(14.34)	(0.07)	(−24.86)
N	10,879,694	10,879,694	4,227,802	4,227,802
Adj. R^2	0.00	0.00	0.01	0.01
Year FE	No	Yes	No	Yes

Table 2.14: Bank Beta Relative to Market Beta After Crises. Table presents time-series regressions at the daily level. The dependent variable is return. Independent variables include the domestic market return and bank return, alone and interacted with indicator variables. $\mathbb{I}$(Zombie) = 1 if the firm is a zombie, and 0 otherwise. $\mathbb{I}$(Post) = 1 if the date is after the BNP event or Sanyo event, and 0 otherwise. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.7.4 Appendix Figures

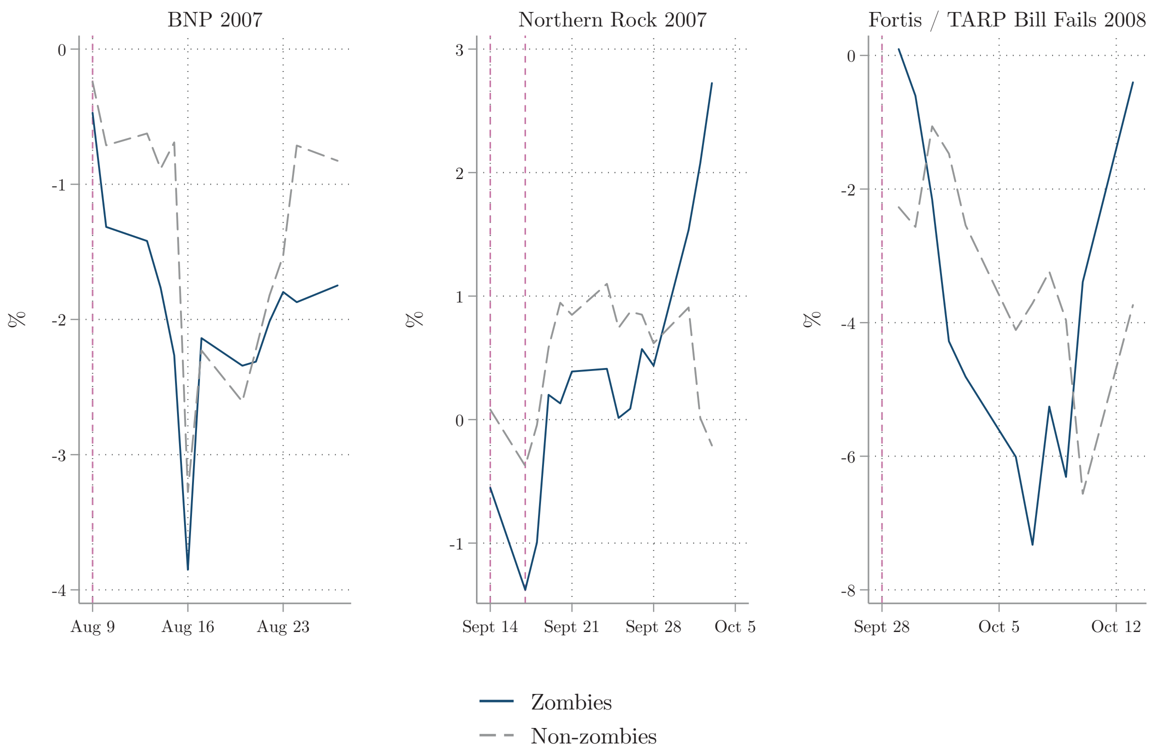


Figure 2.9: Cumulative Abnormal Returns in Europe. Figure shows the value-weighted cumulative abnormal returns for zombies and non-zombies after three events in the Global Financial Crisis.

Chapter 3

Cash-Hedged Stock Returns

Co-authored with Chase P. Ross and Landon J. Ross.

3.1 Introduction

We study the effect of corporate cash holdings on stock returns. Cash is necessary for a firm's operations, and firms use their cash holdings as a means of payment, financing investments, and managing risk. Firms earn different returns on cash and their non-cash assets, and failing to account for cash holdings and the return on cash leads to biases in standard asset pricing frameworks.

Cash is also an economically significant source of time-series and cross-sectional variation in public firms' assets (Figure 3.1). In December 2020, the value-weighted U.S. stock market held roughly 22% of its assets in cash and short-term equivalents compared to approximately 8% on average in the late 1970s. The variation in individual firms' cash share has increased on average almost every decade, with a substantial large peak during the dot-com bubble.

We estimate firm-specific cash returns with a model of the value of cash from Faulkender and Wang (2006). We find the average value of a $1 inside a firm is $0.95, but the value varies considerably over time (Figure 3.2). We calculate a firm's cash-hedged stock return with the firm's stock return, cash return estimate, and our stock return decomposition. We use our firm-level cash return and cash-hedged return to study how cash balances affect portfolio optimization, factor creation, betas, and cross-sectional asset pricing.

We motivate our results with a simple model to show the effect of a firm's implicit cash holding on the investor's portfolio optimization. We decompose a firm's standard stock return into the firm's cash-hedged return, cash share, and return on cash, and we present five main empirical results.

First, we show that standard equity returns are not cash-hedged returns by decomposing stock returns into their cash and non-cash components. Second, we show that common empirical asset pricing factors—size, value, and momentum—have large and time-varying net cash positions. We show that our cash-hedging strategy effectively removes these net cash positions. Third, we show how common empirical asset pricing factors covary with cash holdings; namely, that value strongly covaries with high cash holding. Motivated by this strong covariance structure, we propose the *Cash* factor, which captures the premia between firms with high cash holdings and firms with low cash holdings.

Fourth, we show how to decompose standard betas into the cash-hedged return beta and other components. We perform this beta decomposition for CAPM betas and multifactor betas. We show that the CAPM decomposition provides a securities market line that clearly shows the positive relationship between expected returns and betas. The beta decomposition shows that cash-hedged portfolios will have a more efficient tangency portfolio and a steeper efficient frontier.

Last, we run cross-sectional regressions. We find a significant and positive price of market risk only when using the cash-hedged market factor. Using characteristics instead of betas, we show that firms with higher cash shares have higher expected equity returns and suggest that firms do not hold cash because they think their cash balances will have a strong return.

Related Literature We contribute to the literature that studies how cash affects firm equity returns. A firm's cash holdings may increase firm value. Cash kept on a firm's balance sheet allows firms to finance investments without incurring transaction costs (Miller and Orr, 1966), information asymmetry costs (Myers and Majluf, 1984), agency costs (Jensen and Meckling, 1976), and other costs (Huberman, 1984) associated with raising funds from external capital markets. Cash allows firms to decrease the probability of incurring costs associated with financial distress and bankruptcy when cash flow is inadequate for paying interest and principal on debt obligations (Acharya et al., 2012).

Firms may use cash as an instrument for risk management (Bolton et al., 2011; Acharya et al., 2007). A firm's cash holdings may also decrease firm value. Cash may create differences in the interests of managers and shareholders and allow managers to invest in projects with negative net present value for shareholders but positive benefits for themselves (Jensen, 1986; Richardson, 2006). The benefits of cash for a firm's shareholders also depend on the strength of the firm's corporate governance (Dittmar and Mahrt-Smith, 2007). Additional empirical studies showing cash influences firm value for shareholders are Opler et al. (1999) and Faulkender and Wang (2006). Several other studies[1] also investigate the relationship between cash holdings and firm value.

[1] Some additional studies are Kim et al. (1998), Ozkan and Ozkan (2004), Smith and Kim (1994), Bates et al. (2009), Pinkowitz and Williamson (2007), Foley et al. (2007), Mikkelson and Partch (2003), Dittmar et al. (2003), Almeida et al. (2004), Harford et al. (2008), Denis and Sibilkov (2010), Pinkowitz et al. (2006), Gamba and Triantis (2008), Han and Qiu (2007), Livdan et al. (2009), and Haushalter et al. (2007).

The paper most closely related to the present paper is Palazzo (2012). Palazzo (2012) shows firms' cash holdings may be influenced by the correlation between firm cash flows and aggregate cash flows. The correlation increases cash holdings because financing operations with cash may be cheaper than external financing following adverse aggregate cash flow shocks. The paper uses accounting-based estimates of stocks' expected returns and cross-sectional tests with stock portfolios to evaluate the paper's hypothesized connection between cash holdings and stock returns. Palazzo (2012) is broadly similar to this paper because both study the relationship between firms' cash holdings, firms' expected returns, and aggregate risks. Palazzo (2012) differs from the present paper because the focus of Palazzo (2012) shows the correlation between firm cash flows and aggregate cash flows creates a novel precautionary savings motive for firms. This paper estimates cash and non-cash returns for several established risk factors—market, size, value, and —and studies the cross-sectional properties of the factors' cash and non-cash returns.

3.2 Motivating Model

We describe a simple model to show the effect of a firm's implicit cash holding on the investor's portfolio optimization. We solve the problem with infinite horizon optimal portfolio choice problem, intermediate consumption, no outside income, lognormal stock returns, and independent and identically distributed returns.[2] A representative investor with CRRA utility makes a consumption and portfolio choice between the two assets available, a risk-free bond B_t which pays $r_t dt$ and a firm's stock S_t which follows

$$dR = \mu_S dt + \sigma_S dZ$$

The investor's problem is

$$V(N_0) = \max_{\{c_t,\alpha_t\}_{t=0}^{\infty}} \mathbb{E}_0 \left[\int_0^{\infty} e^{-\rho t} u(c_t) dt \right]$$

$$\text{such that } dN_t = N_t \alpha_t dR_t + N_t(1-\alpha_t) r dt - c_t dt.$$

We model the effect of corporate cash holdings on the firm's stock return by assuming the stock is a portfolio of two assets, the firm's non-cash assets with price E_t and the firm's cash invested in risk-free bonds. The stock's weight on the non-cash asset is $(1-\omega_t)$, and the stock's weight on the risk-free bonds is ω_t. The stock's weight on the risk-free bond asset satisfies $0 \leq \omega_t < 1$. We also assume, for simplicity, ω_t is deterministic with no volatility. We assume the investor observes ω_t, E_t, and B_t. We assume the investor

[2]Section 5.2 of Cochrane (2007) provides details on this special case of the Merton problem and on a number of extensions.

realizes the firm's stock is a portfolio of the firm's risk-free bonds and non-cash assets. The stock's return is a function of the firm's non-cash assets, cash assets, and cash weight

$$dR = (1 - \omega_t)\left(\mu_E dt + \sigma_E dZ\right) + \omega_t r dt.$$

Ito's Lemma and standard arguments yield the investor's optimal portfolio holding of the firm's stock S_t is

$$\alpha_t^\star = \frac{1}{\gamma}\left(\frac{1}{1-\omega_t}\right)\left(\frac{\mu_E - r}{\sigma_E^2}\right). \tag{3.1}$$

Equation 3.1 shows the investor holds the stock S_t in proportion to its Sharpe ratio, and hedges the firm's bond position using leverage. For example, if $\omega_t = 0.5$ then the investor would hedge the bond position by selling a risk-free bond and purchasing additional stock in a ratio that offsets the bond share indicated by ω_t.

For comparison, suppose the investor mistakenly thinks the stock's return follows the process

$$dR = \mu_S dt + \sigma_S dZ_t.$$

where the corresponding optimal portfolio share is

$$\hat{\alpha}_t^\star = \frac{1}{\gamma}\left(\frac{\mu_S - r}{\sigma_S^2}\right). \tag{3.2}$$

When the investor does not account for the effect of cash on the firm's return, the investor's allocation to the stock is too small by a factor of $\frac{1}{1-\omega_t}$ when $1 > \omega_t > 0$. The investor's allocation to the bond is too large.

Equation 3.1 presents two adjustments the investor must make in her portfolio allocation decision. First, she must correctly measure the first and second moments of the true source of risk; the optimal portfolio share depends on the Sharpe ratio of E (using moments μ_E and σ_E) not S (using moments μ_S and σ_S). Second, she must hedge out the stock's implicit risk-free bond position. Figure 3.3 confirms the intuition of the model by plotting α_t as a function of ω_t. When the risky asset available to the investor carries a larger implicit risk-free bond position, the investor must lever up their risky asset allocation to compensate.

3.3 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 firm's cash and a firm's non-cash assets. 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 of a firm's assets except for the firm's cash and has monthly return e_t^i, which we call the *cash-hedged stock return*. Partitioning each stock's value into the two disjoint assets lets us equate a stock's gross return as 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, and partition the return:

$$\begin{aligned} r_t^i &= \left(\frac{\text{Non-Cash Assets}_t^i}{\text{Total Assets}_t^i}\right)\text{Return}_t^{i,\text{non-cash}} + \left(\frac{\text{Cash}_t^i}{\text{Total Assets}_t^i}\right)\text{Return}_t^{i,\text{cash}} \\ &= (1-w_t^i)e_t^i + w_t^i b_t^i. \end{aligned} \tag{3.3}$$

Modeling a stock's return with equation 3.3 gives us a standard accounting identity equating a portfolio's return to the returns of the portfolio's constituent securities. Thus, we can back out unknown variables from the equation's observed variables.

For our empirical analysis, we use the ratio of cash and short-term equivalents to total assets from Compustat to compute w_t^i, and we will use stock returns from CRSP for r_t^i. We use a model from Faulkender and Wang (2006) to help us compute b_t^i, the return on firms' cash assets. The equation's only unknown variable is e_t^i, a firm's non-cash return. We use the following equation to determine a stock's non-cash return from the equation's other variables with known values.

$$e_t^i = \frac{1}{(1-w_t^i)}r_t^i - \frac{w_t^i}{(1-w_t^i)}b_t^i \tag{3.4}$$

Using equation 3.4, we can consider a stock's non-cash return, or its cash-hedged return, e_t^i as the return of a particular portfolio constructed with two hypothetical trades. The first trade buys $\frac{1}{(1-w_t^i)}$ shares of the firm's stock. Since the fraction of a firm's total assets held in cash is between zero and one, the stock's weight in equation 3.4 exceeds one. In other words, the non-cash portfolio's first position is a levered position in the firm's stock. The second trade sells exactly the amount of firm cash, $\frac{w_t^i}{(1-w_t^i)}$, underlying the portfolio's $\frac{1}{(1-w_t^i)}$ units of the firm's stock. The second trade hedges the non-cash portfolio's exposure to the firm's cash associated with the portfolio's long position in 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 implemented with two trades is hypothetical because firms' cash and non-cash assets cannot be individually bought and sold.

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

$$r_t^p = \sum_{i \in p} v_t^i r_t^i = \sum_{i \in p} v_t^i((1 - w_t^i)e_t^i + w_t^i b_t^i). \tag{3.5}$$

The value-weighted non-cash only and cash only portfolio returns—e_t^p and b_t^p— are useful for measuring a stock portfolio's aggregate cash and non-cash returns without cash-share changes contributing to the portfolios' returns. The definitions of the non-cash only and cash only value-weight portfolios are

$$e_t^p = \sum_{i \in p} v_t^i e_t^i \tag{3.6}$$

$$b_t^p = \sum_{i \in p} v_t^i b_t^i \tag{3.7}$$

where v_t^i is asset i's value weight within portfolio p. We define the term $\gamma_t^i = w_t^i(e_t^i - b_t^i)$ 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:

$$\begin{aligned} r_t^i &= e_t^i - w_t^i(e_t^i - b_t^i) \\ &= e_t^i - \gamma_t^i. \end{aligned} \tag{3.8}$$

The equation is helpful for two reasons. First, we can interpret the equation's first term as the stock's return if management saved no cash on its balance sheet; the second term is the cost that management incurs by holding cash 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 γ_t^i), containing variation in the stock's return due to variation in the firm's cash holdings, and another term, e_t^i, that does not.

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:

$$\begin{aligned} r_t^{p,xs} &= \sum_{i \in p} v_t^i r_t^{i,xs} \\ &= \sum_{i \in p} v_t^i (r_t^i - r_t^f) \\ &= \sum_{i \in p} v_t^i ((1 - w_t^i) e_t^i + w_t^i b_t^i - r_t^f) \\ &= \sum_{i \in p} v_t^i (e_t^i - r_t^f - w_t^i e_t^i + w_t^i b_t) \\ &= \sum_{i \in p} v_t^i e_t^{i,xs} - \sum_{i \in p} v_t^i w_t^i (e_t^i - b_t) \\ &= e_t^{p,xs} - \gamma_t^p \end{aligned} \tag{3.9}$$

For reference, Table 3.1 summarizes identities used to decompose stock and portfolio returns into cash and non-cash returns.

3.4 Data

3.4.1 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 Asness et al. (2013b). Our stock sample's construction begins with all U.S. stocks (sharecodes 10 and 11) traded on the NYSE, AMEX, and NASDAQ, with share prices greater than one dollar at the beginning of each month. We exclude REITS, ADRs, preferred shares, financial firms (SIC codes 6000–6799), and we require stocks to have monthly returns for the previous 12 months to construct the momentum characteristic. We require stocks to have book values available six months before the current month, and we require stocks to have share prices and shares outstanding for the previous month and six months ago. 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 also use the market capitalization procedure from Asness et al. (2013b) to create a very liquid collection 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. This procedure creates a sample of large and very liquid stocks. Asness et al. (2013b) 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. However, 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.

We place restrictions on 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. We do not use annual analogs of the quarterly total asset and cash variables. We consider these variables' timeliness for determining the contribution of firms' cash and non-cash returns to their stock returns. Since the most recent annual versions of these variables are potentially 16 months old, the annual variables for fiscal periods too far in the past to reasonably proxy for a firm's current cash share.

We also drop pharmaceutical firms (SIC codes 2830–2836) because these firms' cash holdings are unusually large relative to their total assets. Pharmaceutical firms' unusually large cash-to-asset ratios maybe due to the pharmaceutical industry practicing much more conservative accounting than other industries (Easton and Pae, 2004). Accounting conservatism may prompt these firms to provide pessimistic valuations of assets with uncertain value, like drug research and development, but not easily valued assets, like cash. As a consequence, cash makes up a large fraction of these firms' reported balance sheets. Chandra (2011) also finds that pharmaceutical firms are particularly likely to practice conservative financial accounting because of these firms' greater shareholder litigation risk and the high level of conservatism required by accounting standard Financial Accounting Standard Board (1974) for their research and development activities. Pharmaceutical conservative accounting practices mean their reported net assets are too low (Watts, 2003a,b), and their assets subject to less conservative accounting, like cash, make up too large a fraction of their reported balance sheets.

Our paper's sample begins in January 1976 and ends in December 2020. Both CRSP and Compustat provide data for years before 1976. We do not include earlier years in our sample because the quarterly cash and total asset observations necessary for our cash share variable are missing for approximately 80% of the merged, monthly CRSP–Compustat sample before 1976. 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 requisite variables are not available before 1976.

3.4.2 Variables

We use the variable definitions from Asness et al. (2013b) for the book-to-market and momentum firm characteristics. 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. (2013b) use this specific value definition because it is a standard, conservative, and easily implemented definition of BEME. Fama and French (1992b) provide another common BEME definition with more complex lags than the above definition. The paper's results are similar when using the BEME and market value definitions from Fama and French (1992b). We compute the firm size characteristic as the product of a firm's shares outstanding and share price at the beginning of the current month. We define momentum (MOM) 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 definition of MOM is standard, including our omission of a stock's return over month $t-1$ from the construction of MOM.[3] We use these characteristics to characterize empirical features of stocks' aggregate cash and non-cash returns, so basic definitions of these variables suffice.

We measure a firm's cash share, variable w^i_t in equation 3.3, as the ratio of cash to total assets:

$$\begin{aligned} w^i_t &= \frac{\text{CHEQ}^i_{t-6}}{\text{ATQ}^i_{t-6}} \\ &= \frac{\text{Quarterly Cash and Short Term Equivalents}^i_{t-6}}{\text{Quarterly Total Assets}^i_{t-6}}. \end{aligned} \tag{3.10}$$

where $t-6$ reflects accounting variables for the period six months before. We view a stock's cash share in month t as an unobserved variable and a firm's lagged cash to total asset ratio as a reasonable proxy for a stock's cash share. We later report results supporting our assumption that lagged cash shares proxy

[3] A stock's month $t-1$ return also predicts stock returns and may attenuate the return predictability of MOM. Standard explanations for $t-1$ month return reversals are market microstructure and limited liquidity (Jegadeesh, 1990; Boudoukh et al., 1994).

for current cash shares. We chose a six-month lag for the cash share, consistent with the BEME variable's timeliness. 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. However, 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.

3.4.3 Firm-Level Cash Return Variable Construction

Our procedure for estimating the return on firms' cash has four steps. First, we use the methodology from Faulkender and Wang (2006) to estimate the marginal value of cash for each firm in our sample. Second, we integrate our estimate of the marginal value for a firm's cash to determine the average value of the firm's cash. Third, we compute the return on a firm's cash by dividing the market value of a firm's cash at fiscal year-end by the market value of a firm's cash at the previous fiscal year-end. Last, we create firm-specific cash return mimicking portfolios to estimate cash returns at a higher frequency.

We follow the methodology from Faulkender and Wang (2006) to calculate the marginal value of cash for each firm, and we summarize this methodology below.[4] For the dependent variable in the regression, Faulkender and Wang (2006) use a stock's excess return over a fiscal year t, which is calculated as the stock's return from the beginning to the end of the fiscal year return less the return of a benchmark portfolio over the same year. 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_{t-1}^{i}. 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

[4]See Faulkender and Wang (2006) 1967–1968 for further details.

the firm's cash changes by one dollar. The regression specification from Faulkender and Wang (2006) is

$$\begin{aligned} r_t^i - R_t^{i,B} = \gamma_0 &+ \gamma_1 \frac{\Delta C_t^i}{M_{t-1}^i} + \gamma_2 \frac{\Delta E_t^i}{M_{t-1}^i} + \gamma_3 \frac{\Delta NA_t^i}{M_{t-1}^i} + \gamma_4 \frac{\Delta RD_t^i}{M_{t-1}^i} \\ &+ \gamma_5 \frac{\Delta I_t^i}{M_{t-1}^i} + \gamma_6 \frac{\Delta D_t^i}{M_{t-1}^i} + \gamma_7 \frac{C_{t-1}^i}{M_{t-1}^i} + \gamma_8 L_t^i + \gamma_9 \frac{NF_t^i}{M_{t-1}^i} \\ &+ \gamma_{10} \frac{C_{t-1}^i}{M_{t-1}^i} \times \frac{\Delta C_t^i}{M_{t-1}^i} + \gamma_{11} L_t^i \times \frac{\Delta C_t^i}{M_{t-1}^i} + \varepsilon_t^i. \end{aligned} \tag{3.11}$$

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 Ken French's website. The dependent variable is the firm's return after controlling for the firm's expected return, as calculated using the corresponding 5×5 portfolio. 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.[5]

In the regression, ΔX_t^i equals $X_t^i - X_{t-1}^i$ and 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 3.23 reports regression coefficients for the Faulkender and Wang (2006) regression specification. Our regression results are similar to the results in Faulkender and Wang (2006). Since Faulkender and Wang (2006) provides a detailed discussion and analysis of the regression, we refer interested readers to the original paper's methodology.

Taking the partial derivative of equation 3.11 with respect to ΔC_t^i yields the marginal value of \$1 to firm

[5]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 in this manner 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.

i at time t:

$$\text{Marginal Cash Value}_t^i = \gamma_1 + \gamma_{10}\frac{C_{t-1}^i}{M_{t-1}^i} + \gamma_{11}L_t^i$$
$$= 1.261 + \left(-0.719 \times \frac{C_{t-1}^i}{M_{t-1}^i}\right) + \left(-1.171 \times L_t^i\right)$$

The equal-weighted average marginal cash value across all firms is $1.261 + (-0.719 \times 0.17) + (-1.171 \times 0.20) =$ \$0.90. 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 next dollar would likely have to go toward expenses or debtors.

$$\text{Average Cash Value}_t^i = \frac{1}{C_{t-1}^i}\int_0^{C_{t-1}^i} \text{Marginal Cash Value}_t^i \; dC_{t-1}^i$$
$$= 1.261 + \left(-0.719 \times \frac{1}{2} \times \frac{C_{t-1}^i}{M_{t-1}^i}\right) + \left(-1.171 \times L_t^i\right)$$

We use a firm's average cash value estimates to compute the 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:

$$\text{Fiscal year cash return}_{i,t} = \frac{\text{Average Cash Value}_t^i}{\text{Average Cash Value}_{t-1}^i}. \tag{3.12}$$

Last, 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 30-day, 1-year, 10-year, and 30-year U.S. Treasuries using annual data. We then estimate a firm's monthly cash returns with the mimicking portfolio weights.

3.4.4 Cash-Hedged Stock Return Construction

After estimating firms' cash returns, we have the variables necessary for creating estimates of firms' cash-hedged stock returns. We use firms' monthly stock returns r_t^i, cash-to-total asset ratios (w_t^i, estimated using the six-®month lag of the cash-to-total asset ratio), and monthly cash return estimates (b_t^i). We use the quarterly frequency Compustat variables cash and short-term equivalents and total assets for the cash-to-total assets ratio. We drop from our sample firms with cash-to-total asset ratios that are less than or equal to zero; firms with negative cash and short-term equivalents; and firms with negative total assets. To compute a firm's cash-hedged monthly stock return we substitute the firm's cash return, b_t^i, cash-to-total assets ratio,

w_t^i, and stock return, r_t^i, into the equation

$$e_t^i = \frac{1}{(1-w_t^i)} r_t^i - \frac{w_t^i}{(1-w_t^i)} b_t^i. \tag{3.13}$$

We winsorize the yearly cash return and e_t^i at the 1 and 99 percent levels to reduce the effect of outliers. After estimating firms' monthly cash-hedged stock returns, we construct value-weighted test and factor portfolios using definitions collected in Table 3.1.

3.4.5 Portfolio Construction

Gathering stocks in portfolios sorted on a characteristic is a standard procedure for constructing cross-sectional asset pricing tests dependent variables. All of the portfolios we construct use monthly returns, use value-weights, and are re-balanced 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, similar to Fama and French (1992b). We independently double sort 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 5x5 size and book-to-market portfolios in stock 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 stock return to calculate the value-weighted returns. We follow an analogous procedure to form 10 momentum-sorted portfolios.

3.4.6 Factor Construction

For analysis, we use two approaches to construct factors: the first only uses the sorting variable in a single sort, and the second uses double and triple sorts. Each approach results in long-short self-financing factors. All of the factors use monthly returns, use value-weights, and are re-balanced monthly. Stocks value weights are determined monthly by their beginning of month market capitalizations.

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 five simple factors: *Value*, *Size*, *Mom*, and *Cash* and calculate the standard returns and cash-hedged returns to each trading strategy. The first three factors are constructed using the commonly-used sorting variables of book-to-market, book value, and past returns as discussed in 3.4.2. The sorting variable for *Cash* is a firm's cash share.

Second, we construct *HML*, HML^{Triple}, *SMB*, SMB^{Triple}, *WML*, WML^{Triple}, and $CASH^{Triple}$ using double and triple sorts. *SMB* and *HML* are constructed using the same strategy as Fama and French (1993). We construct *WML* in the same way as *HML*, but using sorts on size and past returns. In this way, all three factors control for size. As in Fama and French (1993), *SMB* is constructed to be largely independent of value, and *HML* is designed to be largely independent of size. Double sorting helps "control" for the fact that high and low value stocks may consistently coincide with higher and lower returns because sorting on value implicitly sorts on another variable that coincides with differential expected returns.

Likewise, we construct triple sorted-factors that "control" for cash share—which we find varies with returns—in addition to size. To construct HML^{Triple} we perform independent sorts on cash share (Flush/Mid/Pennies), size (Big/Midsize/Small), and book-to-market (HiBM/MidBM/LoBM), and then construct the triple-sorted factor. To be explicit, the equation for HML^{Triple} is below. As we discuss later, the results suggest that it is important to triple sort to construct the cash factor $CASH^{Triple}$ because cash holdings and value strongly covary.

$$
\begin{aligned}
HML^{Triple} = & \frac{\text{HiBM/Flush/Big + HiBM/Mid/Big + HiBM/Pennies/Big}}{6} \\
& + \frac{\text{HiBM/Flush/Small + HiBM/Mid/Small + HiBM/Pennies/Small}}{6} \\
& - \frac{\text{LoBM/Flush/Big + LoBM/Mid/Big + LoBM/Pennies/Big}}{6} \\
& - \frac{\text{LoBM/Flush/Small + LoBM/Mid/Small + LoBM/Pennies/Small}}{6}
\end{aligned}
$$

The remaining triple-sorted factors are constructed analogously.

3.5 Results

First, we show that standard equity returns are not cash-hedged returns by decomposing stock returns into their cash and non-cash components. Second, we show that common empirical asset pricing factors—size, value, and momentum—have large and time-varying net cash positions. We show that our cash-hedging strategy effectively removes these net cash positions. Third, we show how common empirical asset pricing factors covary with cash holdings; namely, that value strongly covaries with high cash holding. Motivated by this strong covariance structure, we propose the *Cash* factor that captures the premia between firms with high cash holdings and low cash holdings.

Fourth, we show how to decompose standard betas into the cash-hedged return beta and other components.

We perform this beta decomposition for CAPM betas and multifactor betas. The CAPM decomposition provides a securities market line that clearly shows the positive relationship between expected returns and betas. The beta decomposition shows that cash-hedged portfolios will have a more efficient tangency portfolio and a steeper efficient frontier.

Last, we run cross-sectional regressions. We find a significant and positive price of market risk only when using the cash-hedged market factor. Using characteristics instead of betas, we show that firms with higher cash shares have higher expected equity returns and suggest that firms do not hold cash because they think their cash balances will have a strong return.

3.5.1 Stock Portfolio Return Decomposition

Table 3.2 reports summary statistics for book-to-market, size, momentum, and cash-to-total asset portfolios. The portfolios are constructed by sorting stocks into terciles (P1, P2, and P3), and P3-P1 is the spread between the top and bottom terciles. We calculate each portfolio's stock return and the separate the non-cash and cash components of the overall stock return. For each portfolio p, the non-cash return is calculated as $\sum_{i \in p} v_t^i (1 - w_t^i) e_t^i$, and the cash return equals $\sum_{i \in p} v_t^i w_t^i b_t^i$.

The table reports the portfolios' average return, standard deviation, annualized Sharpe ratio, and the alpha and t-statistic from time-series regressions of the portfolio's return on the market return. The t-statistics use Newey-West standard errors with ten lags.

The stock portfolios' average returns and other statistics are consistent with the previous literature using the same characteristics. Looking across the low to high portfolios, we can broadly see the value and momentum effects. The value and momentum effects have smaller t-statistics than usual due to our use of a sample of large and liquid stocks.

The non-cash and cash return columns indicate the bulk of the stock returns come from the non-cash return component. The cash components are smaller returns, with values around 0.05%, and the portfolios' non-cash component is slightly larger than the portfolios' stock returns.

Table 3.3 reports the average non-cash and cash returns for each tercile. These returns are formed using firms' non-cash and cash returns and equations 3.6 and 3.7. We do not scale the returns by firms' cash-shares, which distinguishes the returns from the non-cash and cash component returns reported in Table 3.2.

Compared to stock returns formed on the same characteristics, the non-cash returns are slightly larger in magnitude and are more volatile, but the Sharpe ratios and alphas are in a similar range. The cash portfolios' returns are noticeably larger than the cash return component of stock returns in Table 3.2, but, overall, the cash portfolios' returns are small relative to the non-cash portfolios returns.

Table 3.4 reports summary statistics on the cash share of each tercile portfolio. For a given month t and value-weight portfolio p, the portfolio's cash-share is $\sum_{i \in p} v_t^i w_t^i$. The table reports time-series averages and standard deviations of the portfolios' monthly cash-shares. Unsurprisingly, cash-to-total asset portfolios' cash shares increase considerably, from 0.02 for the low portfolio up to 0.25 for the high portfolio. The average cash-share decreases from the low to the high book-to-market portfolio. The other sorting variables have a weaker correlation with firms' cash shares. Across size portfolios, the average cash share is flat; and across momentum portfolios, cash share increases slightly.

3.5.2 Stock Returns Differ from Non-Cash Returns

What is a firm's stock return? An inspection of Equation 3.3 makes it clear that r_t^i, the firm's stock return, is a firm's non-cash return only under the unlikely event a firm carries no cash or other short-term equivalents: that is, $r_t^i = e_t^i$ if and only if $w_t^i = 0$. The stock return r_t^i is less than return of a public firm's non-cash return. Specifically, if $\mathbb{E}e_t^i > \mathbb{E}b_t^i$, then Equation 3.3 shows:

$$\begin{aligned}
\mathbb{E}r_t^i &= \mathbb{E}\left[(1 - w_t^i)e_t^i + \omega_t^i b_t^i\right] \\
&\leq \mathbb{E}\left[(1 - w_t^i)e_t^i + w_t^i e_t^i\right] = \mathbb{E}e_t^i
\end{aligned}$$

Similarly, in the aggregate market, $r_t^{m,xs} = e_t^{m,xs} - \gamma_t^m$, so the aggregate stock market return is less than the aggregate non-cash market return.

Table 3.5 shows summary statistics for the stock market excess return, market non-cash excess return, market cash excess return, and the value-weighted market cash share. For the market-level aggregate returns, the average monthly non-cash return is 1.06% and larger than the average stock return of 0.76%, as predicted. The Sharpe ratio for the cash-hedged market return is about 20% larger, with the 40% increase in average return offset by larger volatility. This is sensible since the stock returns had an implicit investment in cash, which is a low volatility asset.

Table 3.6 confirms that firms' non-cash excess returns are greater than stock excess returns on average, both at the firm level (column 1) and at the aggregate market level (columns 2 and 3). The table reports the regression of the standard stock excess returns on non-cash excess returns. If the stock excess return is less than the non-cash excess return, the coefficient in this regression will be less than one. The regression's coefficient is 0.71 in the firm-level regression and significantly different from zero. The regression at the aggregate market level yields similar results: the coefficient is 0.82 in our sample and 0.72 using Fama–French's market excess return. This means that for a one percentage point increase in non-cash return, the stock return increases by less than one percentage point.

3.5.3 Cash-Adjusted Factor Premia

Table 3.7 presents the returns for the most common asset pricing factors when calculating returns and volatilities for the standard stocks and separately for the cash-hedged returns, which corresponds to the standard return and the cash-hedged return. Figure 3.4 presents the cumulative returns for standard and cash-hedged *HML* and *WML*.

We find that comparing the standard measure against the cash-hedged measure flips the sign of value to negative. A similar phenomenon appears for *HML*, in which in standard terms carries a 1.46% average excess return, but when adjusted for its cash holdings has a −2.37% average monthly excess return. Table 3.8 shows the average cash share for each of the 25 size- and BEME-sorted portfolios. Within each size bucket, the cash share monotonically increases as we move from value portfolios to growth portfolios. The results suggest that growth stocks have lower returns because they have larger cash shares and thus a larger implicit investment in the risk-free bond, which drags the overall return down for growth stocks. Value stocks outperform growth stocks–in standard returns–in the same way a 95% stock/5% bond portfolio outperforms an 80%/20% portfolio.

The differential cash holding between growth and value means growth stocks will grow proportionally more as the investor hedges out the larger cash share: since growth stocks have a larger implicit holding of a low-return investment, moving from standard returns to cash-hedged returns will change the mean and standard deviation of growth stocks. Of course, average cash-hedged returns and volatility should also increase for value stocks, but to a lesser extent. In Table 3.21, we can see this: comparing standard to cash-hedged returns, the mean and standard deviation of growth stocks increase more than that of value stocks. Thus, in standard terms, value outperforms growth; but in cash-hedged terms, growth outperforms value.

Looking at the mean and standard deviation together, it appears that as cash-hedged returns increase—going from value to growth—volatility also increases. This relationship is in line with the simple idea that returns are compensation for risk. In contrast, looking at standard returns, value stocks have higher returns and *less* volatile returns. This result suggests that cash share helps us refine our understanding of the value premium as compensation for risk.

These results strongly suggest that there is a strong covariance between value and cash, and thus it is crucial to triple sort value when looking in cash-hedged terms. Looking back at Table 3.7, HML^{Triple} maintains the positive mean return and Sharpe ratio when we look between standard returns and cash-hedged returns.

3.5.4 Cash-Related Covariance in Common Asset Pricing Factors

We test how common asset pricing characteristics covary with cash holdings by sorting each stock at each point in time into percentiles for size, book-to-market, momentum, and cash share separately. We then regress the cash share percentile on the percentile for size, value, and momentum in Table 3.9. The table shows that cash holdings negatively covary with size and value and positively covaries with momentum. In other words: larger firms hold less of their assets in cash; firms with higher book equity-to-market equity ratios hold less of their assets in cash; and, firms with high momentum have a larger cash share. Most notable is the magnitude of the covariance: cash share and value have a large negative coefficient of -0.332, nearly twenty times larger than the negative correlation between cash share and size. We get similar results for value and momentum when we regress the change in a firm's cash share percentile on the change in a firm's characteristic percentile.

The covariance between cash holdings and value motivates triple sorting of *HML*, *SMB*, and *WML* to control for cash. We report summary statistics for the triple sorted factors in Table 3.7 which shows that after triple sorting *HML* the value premium nearly triples. Controlling for cash for *SMB* and *WML* do not appear to have a significant effect on their average standard returns.

Additionally, we test covariance via spanning tests: we regress each factor on the other candidate factors from standard pricing models. If a factor is not spanned by other factors, it will have a statistically significant intercept and therefore should be included in our pricing model. Table 3.10 presents the spanning tests for the Fama–French 3 factor model with a momentum factor. These factor returns are in standard terms. Scanning across the constant terms, we can see that only *SMB* is spanned by the other factors, as each other factor has a statistically significant intercept. Therefore, each factor except for *SMB* is not spanned by a linear combination of the other factors, consistent with the asset pricing literature consensus that size, without adjustments, is a marginally significant anomaly.

Table 3.11 presents the spanning tests for the cash-hedged factors. Again, *SMB* is spanned by the other hedged factors. *HML*'s constant is marginally significant. Since our sample ends in early 2021—which coincides with a large drawdown in value—we expect that the *HML* constant will become positive again as the cycle continues.

The cash factor and *HML* have a strong negative covariance. Table 3.12 presents the spanning tests for the cash-hedged factors in the previous table, and the *Cash* factor. Importantly, all of the factors significantly load and covary with *Cash*, and the *Cash* factor has a large significant coefficient and a strong negative covariance with *HML*. This table motivates an asset pricing model with a cash factor or an asset pricing model in which the factors control for their implicit cash holdings. As in the previous spanning tests, *SMB* is spanned by the other factors.

3.5.5 Factor Legs Have Varying Cash Holdings

Firm cash holdings bias factor returns constructed from sorts on a characteristic like size, book-to-market, and momentum. We can decompose the returns to the factor, long, and short portfolios into the returns to the constituent firms' equity and cash holdings. Let f_t be the 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:

$$f_t = r_t^L - r_t^S \tag{3.14}$$

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

$$f_t = (e_t^L - e_t^S) - (\gamma_t^L - \gamma_t^S) \tag{3.15}$$

The first term, $e_t^L - e_t^S$, denotes the return of the cash-hedged components of the factor's long and short portfolios and is typically the term of interest when constructing a factor from a characteristic sort's high and low portfolios. The last term, $\gamma_t^L - \gamma_t^S$, describes bias in the factor's realizations due to firm cash holdings in the long and short legs.

Figure 3.5 shows there is considerable time variation in the net cash position of factor portfolios constructed size, value, and momentum. The value factor portfolio's negative time series values mean stocks in the sort's low portfolio have larger cash holdings than stocks in the sort's high portfolio. The momentum portfolio typically contains a long but volatile cash position. The size factor portfolio's net cash holding is the smallest of all three characteristics. However, the size factor's net holdings also appear to exhibit long-lived trends up and down in the factor's net cash.

Table 3.13 reports the results of regressing each factor's net cash position on a constant; the coefficient is the average net cash holdings for each factor portfolio. Importantly, this provides a test of whether the factor's net cash position is statistically different from zero. The table's results are in line with the time series figures. The value factor has a significant, negative average net cash position. The momentum factor has a significant, positive average net cash position.

We report empirical results for size, book-to-market, and value factor portfolios constructed after adjusting for their estimated cash holdings in Figure 3.6 and Table 3.14. These results show using our estimate of cash holdings of the high and low characteristic portfolios' cash holdings suffices for reducing the effect of firm cash holdings on the factor portfolios. The average net cash holdings for the cash-adjusted value, size, and momentum factor portfolios remain close to zero in Figure 3.6. We also test if the cash-adjusted factor portfolios' average net cash is significantly different from zero and report the results in Table 3.14. The average net cash position of the cash-adjusted factor portfolios is not significantly different from zero for the size, value, and momentum characteristics. Therefore, we conclude that hedging cash holdings by using our conservative measure of what is known to investors effectively hedges out implicit cash holdings implicit in these portfolios.

3.5.6 Decomposing Standard Betas

In this section, we show the relationship between the standard time-series beta and the cash-hedged beta. We study both a one-factor CAPM model and an expanded multifactor model, and we show that cash holdings affect both betas and expected returns. In particular, the effect of cash attenuates beta estimates, and using cash-hedged returns produces betas with more heterogeneity which leads to better estimates of risk prices.

CAPM Beta Decomposition

We calculate the excess returns of each portfolio, $r_t^{p,xs}$, and the market-level excess standard stock return, $r_t^{m,xs}$, using the equations from Section 3.3. We can decompose the standard stock 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. This is derived in the equation below.

$$\begin{aligned} \underbrace{\beta^{p,standard}}_{\text{standard stock beta}} &= \frac{Cov(r_t^{p,xs}, r_t^{m,xs})}{Var(r_t^{m,xs})} \\ &= \underbrace{\left(\frac{Cov(e_t^{p,xs}, e_t^{m,xs})}{Var(e_t^{m,xs})}\right)}_{\substack{\text{cash-hedged beta} \\ =\beta^{p,cash-hedged}}} \underbrace{\left(\frac{Var(e_t^{m,xs})}{Var(r_t^{m,xs})}\right)}_{\text{ratio of variances}} \\ &+ \frac{-Cov(\gamma_t^p, e_t^{m,xs}) - Cov(e_t^{p,xs}, \gamma_t^m) + Cov(\gamma_t^p, \gamma_t^m)}{Var(r_t^{m,xs})} \end{aligned} \tag{3.16}$$

For each portfolio, the market beta calculated using a time series regression is equivalent to the sum of the parts using the decomposition above. In addition, intuitively, if all companies held no cash ($w_t^i = 0$ for all i) then the market beta and the cash-hedged beta are equivalent, and the standard return and cash-hedged return are also equal.

Figure 3.7 shows the Securities Market Line (SML), with the standard returns of the 25 size and book-to-market portfolios on the y-axis and the market beta of each portfolio on the x-axis. As reported in the literature, the SML is flat and betas and expected returns fail to line up linearly in a positively sloped line. The right panel of Figure 3.7 shows the SML for cash-hedged returns. Now, there is a stronger linear relationship between average cash-hedged betas and expected cash-hedged returns. The results suggest that adjusting standard returns for cash holdings brings basic empirical asset pricing facts to be consistent with basic CAPM intuition that the only measure of risk that is relevant for pricing securities is covariance with the market, which has served as the foundation of asset pricing over the last 60 years.

Table 3.15 shows the empirical beta decomposition. Looking at the averages row, it appears that $\beta^{standard}$ and $\beta^{cash-hedged}$ are very similar. The ratio of the variances is equivalent for all portfolios since we compute both parts at the market-level. The ratio of 1.51 indicates that the aggregate cash-hedged return is 51% more volatile than the standard aggregate return.

Figure 3.8 shows the cash-hedged and standard beta for each portfolio and the difference between the two betas. In each size bucket, the result is consistent: portfolios with the largest and smallest value numbers have the biggest difference between $\beta^{standard}$ and $\beta^{cash-hedged}$. Moving from growth to value in each size bucket, it switches from $\beta^{standard} < \beta^{cash-hedged}$ to $\beta^{standard} > \beta^{cash-hedged}$. It is unsurprising that the most extreme value portfolios have the largest discrepancy: as we discussed previously, there is a strong covariance between cash share and value as growth stocks tend to have high cash share and value stocks tend to have low cash share. Ultimately, even though there is no difference in beta on average, there is a differential effect on beta depending on the portfolio's BEME. Since growth stocks have the largest cash share and the most negative difference in beta, this suggests that cash shares attenuate the standard market beta relative to the cash-hedged market beta ($|\beta^{standard}| < |\beta^{cash-hedged}|$).

The CAPM beta decomposition shows that cash holdings affect both beta and expected returns, leading to the substantial change in the securities market line. When firms choose their cash holdings, they are also implicitly choosing their expected returns and beta.

Multivariate Beta Decomposition

We can extend the beta decomposition to the multivariate factor model. We will focus on the Fama–French 3 factor model. We use the Frisch-Waugh-Lovell Theorem (FWL) to produce an equation of each factor's standard beta as a function of the factor's cash-hedged beta and the adjustment term. Below, we have described the process for *HML*, but 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 will use the following FWL procedure to decompose the *HML* standard stock 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:

$$\begin{aligned}
\underbrace{\beta^{p,HML,3factor}}_{\substack{\text{HML standard}\\ \text{stock beta}}} &= \frac{cov(\tilde{r}_t^{p,xs}, \tilde{r}_t^{HML})}{var(\tilde{r}_t^{HML})} \\
&= \underbrace{\left(\frac{cov(\tilde{e}_t^{p,xs}, \tilde{e}_t^{HML})}{var(\tilde{e}_t^{HML})}\right)}_{\substack{\text{HML cash-hedged beta}\\ =\beta^{p,HML,cash-hedged,3factor}}} \underbrace{\left(\frac{var(\tilde{e}_t^{HML})}{var(\tilde{r}_t^{HML})}\right)}_{\text{ratio of variances}} \\
&+ \frac{-cov(\tilde{\gamma}_t^p, \tilde{e}_t^{HML}) - cov(\tilde{e}_t^{p,xs}, \tilde{\gamma}_t^{HML}) + cov(\tilde{\gamma}_t^p, \tilde{\gamma}_t^{HML})}{var(\tilde{r}_t^{HML})}
\end{aligned} \tag{3.17}$$

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 3 factor Fama-French model can be formed switch out the parts in x_z and β_z.

Tables 3.16, 3.17, and 3.18 show the multivariate beta decompositions for the market factor, the size factor, and the value factor, from the 3 factor model. For the market factor decomposition, the results are similar to the decomposition of the market beta using the CAPM model. For *SMB*, the cash-hedged beta and standard beta are similar.

For the value factor decomposition, the results suggest a large difference between the standard *HML* factor and the cash-hedged component of the *HML* factor, which filters to the betas. On average, the 25 portfolios have a *HML* beta of 0.10, but a cash-hedged *HML* beta of 0, meaning the volatility and adjustment terms do not offset each other as much as in the previous results. In addition, the cash-hedged component of *HML* is 75% more volatile than the standard factor.

Figure 3.9 shows the decomposition of the market standard beta from the 3 factor model against the expected returns. As in the univariate CAPM model, we fail to find a positive linear relationship. However, once we adjust all returns to be in cash-hedged terms, as we do in the right panel, we recover a positive, linear relationship between portfolios' expected returns and market cash-hedged beta. Figure 3.10 shows a similar pattern for the size factor.

For value, we also see a flat relationship between *HML* standard beta and expected returns in Figure 3.11; but for the cash-hedged returns and betas, there is a negative linear relationship. It is clear that cash-adjusted growth stocks outperform cash-adjusted value stocks, which has implications for the value premium and the explanations for the value premium in the literature. The results in Figure 3.11 imply that if we formed our value factor as Low minus High, rather than High minus Low, the relationship would be positive and linear.

Figure 3.12 plots the standard beta and cash-hedged beta for each of the three factors, and Figure 3.13 plots the difference between the betas for each factor. For the size and market factors, growth stocks tend to have a smaller standard beta than cash-hedged beta, and value stocks tend to have a smaller cash-hedged beta than standard beta. However, for the value factor, the cash-hedged beta is smaller than the standard beta for each of the 25 portfolios. The figures again highlight the negative covariance between value and cash holdings.

3.5.7 Efficient Frontier

Investors can benefit from using cash-hedged portfolios for two reasons. First, cash-hedging produces a richer covariance structure across test portfolios by eliminating the correlation across portfolios due to shared exposure. Second, cash-hedging produces a larger variation in the cross-section of expected returns, which is important if the investor is concerned they have poorly sorted their test portfolios or are unsure of which characteristics to use as sorting variables. These two issues suggest that the cash-hedged efficient frontier is steeper than the standard returns efficient frontier, and therefore the cash-hedged tangency portfolio is more efficient than the standard return tangency portfolio.

An immediate consequence of cash-hedging portfolios is that the difference in expected returns across portfolios will grow so long as the portfolios have different amounts of cash holdings, which is empirically true across many batches of single, double, and triple sorts. Why? Suppose ten portfolios have the same average return but with considerable variance in their average cash holdings. When we estimate the portfolios' standard market CAPM beta, each portfolio will have approximately the same beta, and the cross-sectional regression may struggle to find a significant slope between betas and expected returns. However, when you cash-hedged these same portfolios, there will be variation in cash-hedged returns even if the standard expected returns across portfolios are equivalent purely because the differential cash holdings will require the investor to differentially lever up the portfolios proportional to their cash share.

A second advantage to using cash-hedged returns is to protect against lousy sorting. What if investors poorly sorting stocks into test portfolios? If an investor sorts portfolios according to some arbitrary characteristic, then the cross-sectional regressions will struggle to find a significant price of risk for their risk factor of preference.

But we argue the investor can better detect priced risk factors by using cash-hedged returns. This is because hedging out the cash implicit in portfolios will both give the investor a larger spread in expected returns—so long as the portfolios have differential cash shares—and additionally the portfolios will have a richer covariance structure because the share of each portfolio invested in cash will bias the correlation of portfolios' standard returns upwards.

This logic generates a prediction: with poorly-sorted portfolios, the tangency portfolio calculated from standard returns will have a lower Sharpe ratio than the tangency portfolio formed from the same portfolios cash-hedged returns. To be concrete, by poorly sorted we mean little variation in the expected returns across the portfolios. If, however, portfolios are sorted in a way that generates substantial differences in expected returns in unhedged returns, the tangency portfolio improvement using hedged returns will be smaller. In this sense, using cash-hedged portfolios serves as a hedge against poorly-sorted portfolios.

We now provide an example. First, we sort portfolios into nine size and book-to-market portfolios. This sorting allows for a large difference in expected returns across the portfolios. We calculate both standard and cash-hedged returns for these portfolios, where the latter hedge out the implicit cash holding of each portfolio. Figure 3.14 plots the resulting tangency portfolio using both the standard and cash-hedged returns. Table 3.19 provides the summary statistics for the portfolios: the annualized Sharpe ratio is 0.63 for the standard return portfolios and 0.69 for the cash-hedged portfolio, roughly a 10% increase in efficiency.

To test the implications of lousy sorting, we sort stocks into 26 portfolios based on the first letter of their ticker and look at the first 13 letter portfolios. In order for a test of CAPM to work in pricing these portfolios, we need considerable variation in expected returns. Since we have poorly sorted stocks, each portfolio's expected return is approximately the market's return with an error term. Effectively, we have nearly-random samples of the market.[6] Thus, there is little variation in the cross-sectional of expected

[6]Of course, some risk factors may covary with tickers starting with certain letters for a good reason—or some other subtle

returns for these portfolios, and if we run the standard cross-sectional CAPM regression on these portfolios, we will not find a significant price of risk. However, insofar as these ticker portfolios have meaningfully different cash shares—which they empirically do—we can now scale the small difference in their average stock return by their cash shares. This scaling allows us to create more dispersion in expected returns across these poorly sorted portfolios and allows us to reduce the correlation across these portfolios by eliminating their shared covariance stemming from the return of risk-free bonds implicit in their cash holdings (Table 3.19). Figure 3.15 shows the result of calculating the tangency portfolio on these poorly-sorted portfolios: now, the difference in the efficiency of the tangency portfolio is large. The annualized Sharpe ratio for the tangency portfolio using standard returns is 0.80, whereas the cash-hedged portfolio is 21% more efficient with a Sharpe ratio of 0.97.

3.5.8 Cross-Sectional Asset Pricing Results

We now implement the CAPM model using the two-stage asset pricing regressions. In expected return-beta terms, we first implement the time-series regression:

$$R^i = a_i + \beta_{i,a} f_t^a + \beta_{i,b} f_t^b + \ldots, i = 1, \ldots, N, t = 1, \ldots, T \tag{3.18}$$

where f is a factor which proxies the stochastic discount factor, index i indicates each test portfolio and t indicates time. This regression relates a portfolio's return with its exposure to the various proposed factors, and estimates β's for each test portfolio. In particular, CAPM posits that f is equal to the return on the market portfolio.

The second regression is the cross-sectional regression:

$$\mathbb{E}R^i = \gamma + \beta_{i,a}\lambda_a + \beta_{i,b}\lambda_b + \ldots, i = 1, \ldots, N \tag{3.19}$$

The cross-sectional regression provides estimates of the price of risk for a given factor. Our main focus will be on the price of market risk, λ_{Mkt}. More generally, a good factor pricing model will feature an economically small and statistically insignificant intercept γ, a stable and significant price of risk across many sets of test portfolios of different assets, and an economically small and jointly zero pricing errors a_i across all test portfolios. The second test implies that we will reject CAPM if λ_{Mkt} is statistically negative and less than zero. We will check the third test by examining the Gibbons-Ross-Shaken test statistic, which tests whether the a_i from the time-series regressions are jointly zero.

pattern may exist— but we are abstracting away from this to make a simple illustrative point.

Table 3.20 presents the results from the cross-sectional regression for the 25 size- and book-to-market-sorted portfolio and 10 momentum-sorted portfolios. The first two columns test the CAPM model—column one is in standard terms and column two cash-hedged terms—and the last two columns test a model with four factors: the market, *HML*, *SMB*, and *WML*.

The cross-sectional test reveals two facts. First, the price of risk for the cash-hedged market is both significant and positive (1.08 with a GMM t-statistic of 1.94), whereas the standard market price of risk is not statistically different from zero (0.63 with a t-statistic of 1.3). The cash-hedged price of risk is economically large: a one standard-deviation increase in beta corresponds to an increase of 2.16 percentage points annually.

Second, although the price of market risk is marginal in the four-factor model, each price of risk point estimate is larger using cash-hedged terms relative to the standard terms. As shown in the beta decompositions, cash in standard portfolios attenuate beta estimates, which attenuates cross-sectional price of risk estimates. The expected positive slope between betas and expected returns is clear only after hedging cash holdings.

Characteristic Cross-Sectional Regressions Table 3.22 shows firm-level cross-sectional regressions using characteristics. Columns 1 and 2 show that firms with higher cash shares have higher expected equity returns, consistent with our finding of a strong return on the cash factor. Switching from no cash on the balance sheet to 100% cash reflects a 1.3% increase in a firm's monthly equity return. Cash-hedged returns in columns 3 and 4 are mechanically higher when cash share is higher.

Firms hold cash for many reasons. One way to categorize the reasons is based on their anticipated return on cash: firms may hold cash because they think they can earn a high return on cash based on good management; alternatively, firms may hold cash that earns a low return in order to have precautionary savings or avoid financing. Table 3.22 indicates that firms with higher cash shares face lower average returns on cash, which suggests that firms hold cash despite the lower returns.

3.6 Conclusion

Firms hold cash on their balance sheet, and an investor with a position in that firm's stock implicitly holds a position in the firm's cash position. We produce a model to motivate the effect of a firm's implicit cash holding on portfolio optimization. We decompose a firm's standard stock return into the firm's cash-hedged return, cash share, and return on cash.

We show that standard stock returns are not cash-hedged returns: standard stock returns are lower on average and less volatile. Common asset pricing factors also have time-varying and non-zero net cash positions, and hedging out these implicit cash positions change factor premia. In the cross-section, cash holdings affect both returns and betas, and the price of cash-hedged market risk is positive and significant.

3.7 Figures

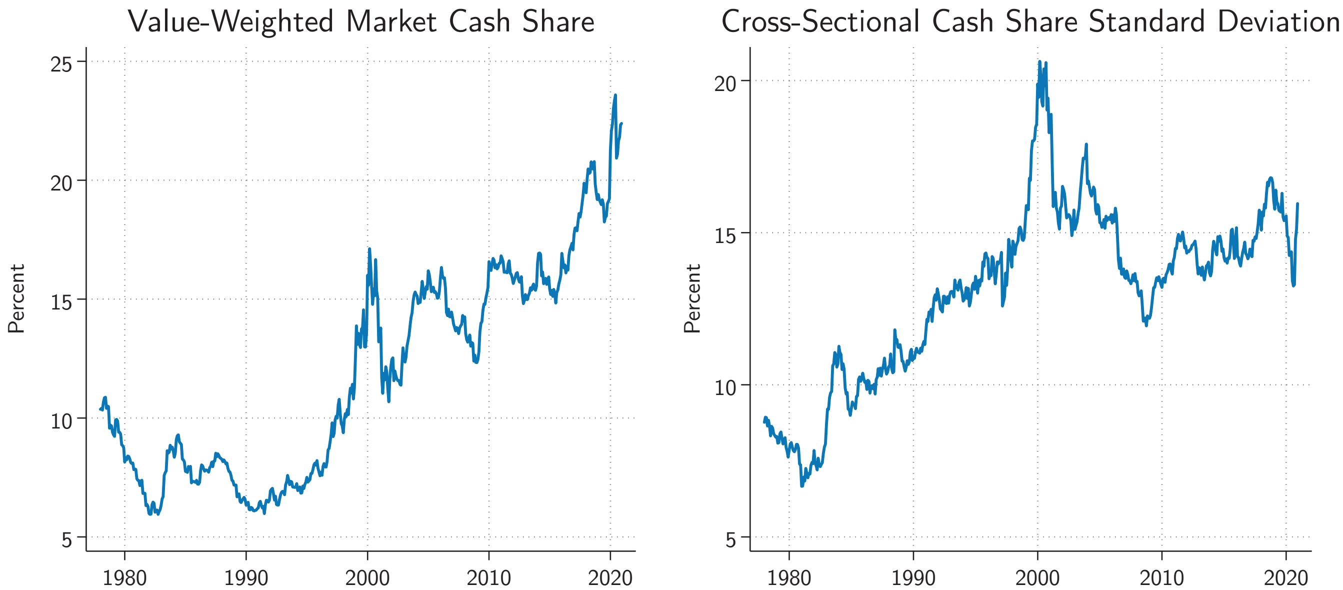


Figure 3.1: Aggregate market cash share and cross-sectional cash share standard deviation. The left panel reports the time-series of the aggregate market's value-weighted cash share from 1978 to 2021. The cash share is the share of cash and short-term equivalents as a percent of total assets. The right panel reports the cross-sectional standard deviation in cash-share across firms in each month.

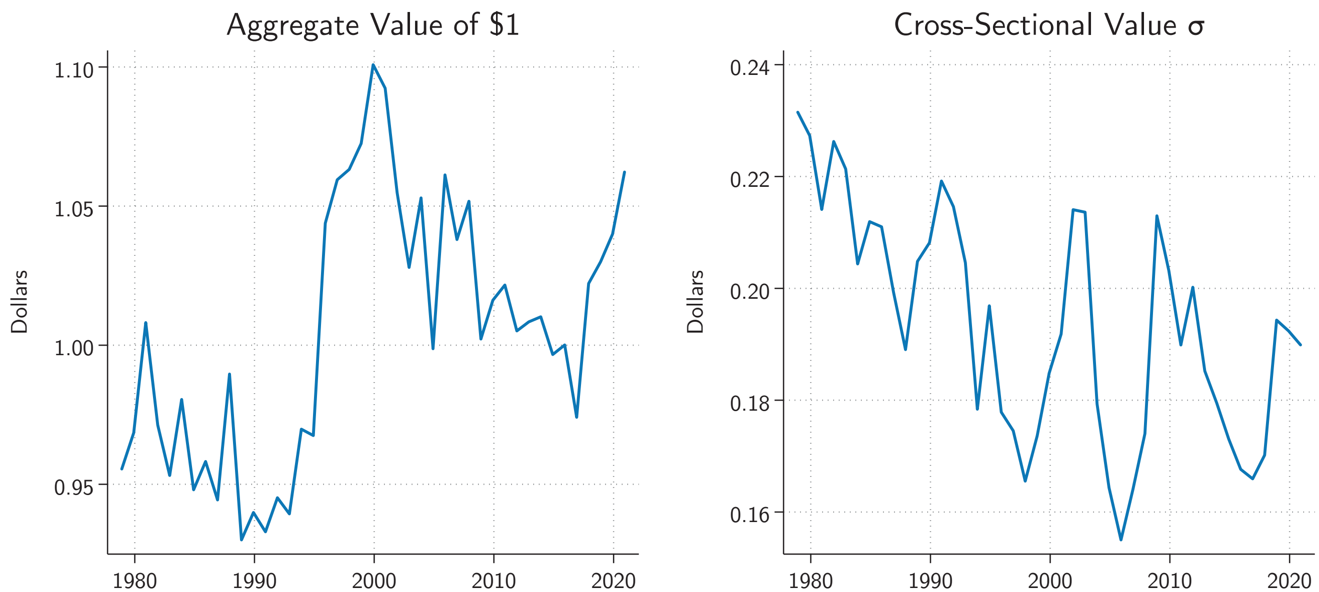


Figure 3.2: Aggregate market average value of $1 and its cross-sectional standard deviation. The left panel reports the time-series of the aggregate market's value-weighted cash share from 1978 to 2021. The cash share is the share of cash and short-term equivalents as a percent of total assets. The right panel reports the cross-sectional standard deviation in cash-share across firms in each month.

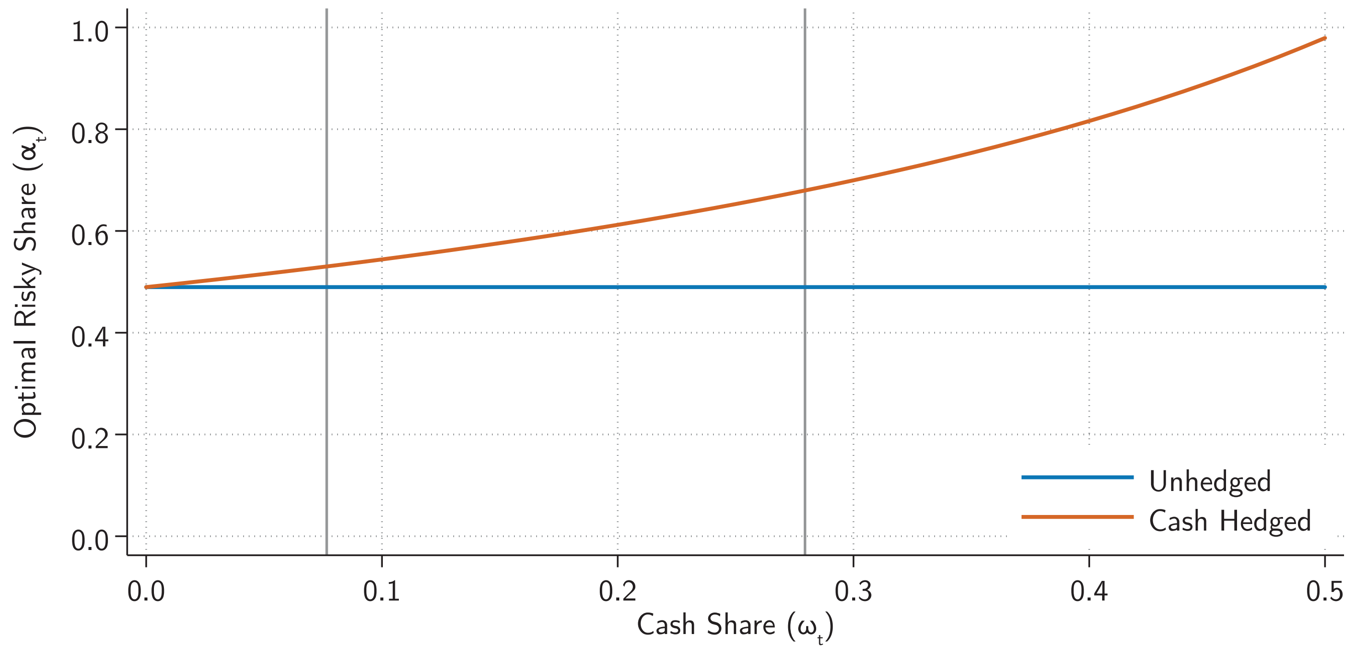
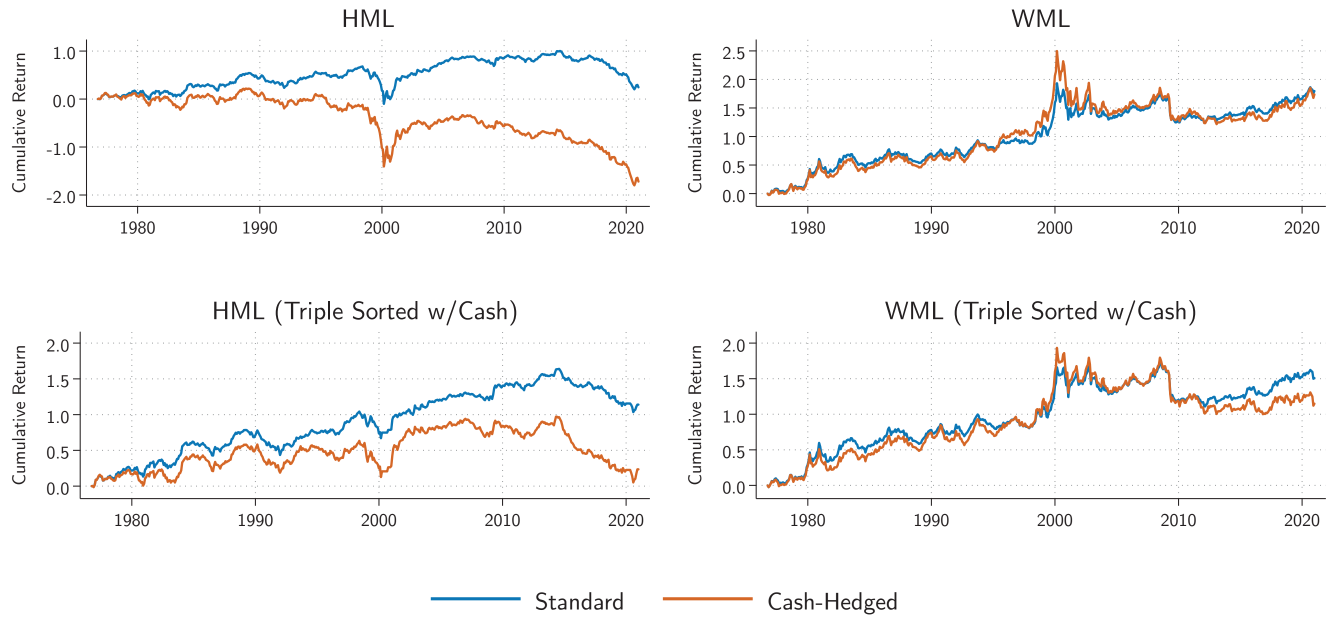


Figure 3.3: Optimal portfolio allocation to risky asset. Assumes CRRA utility, $\gamma = 10$, $\mu_E = \mu_S = 1.1\%$, $\sigma_E = \sigma_S = 4.7\%$. Vertical grey lines mark empirical minimum and maximum cash share for the value-weighted market portfolio.



Note: Cumulative return is sum of log returns.

Figure 3.4: Cumulative returns for value and momentum. Figure plots the cumulative return—defined as sum of log returns—for both *HML* and *WML* in standard and net cash terms. Top panel does not triple-sort cash holdings, while bottom panel does.

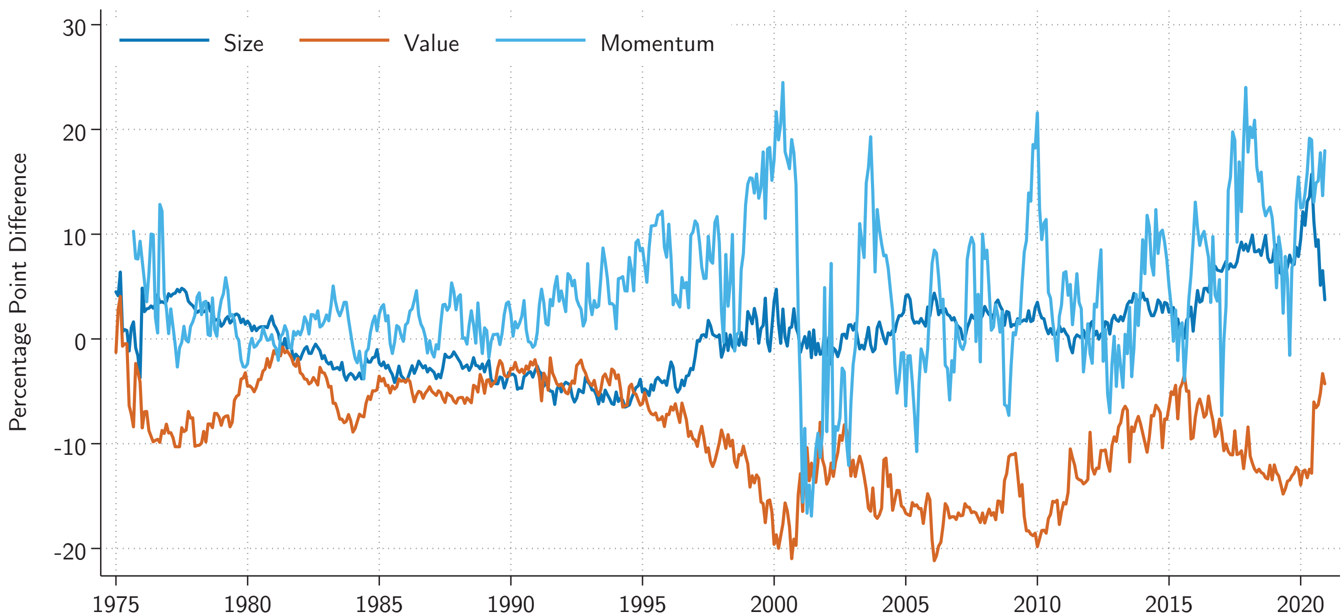


Figure 3.5: Factor portfolios' net cash holdings. This figures report time series of net cash holdings for factor portfolios constructed on the size, book-to-market, and momentum characteristics. In other words, the figure shows the difference between the cash share of the long leg less the cash share of the short leg. Notice: the cash share is measured at the same time as the return, and hence deviates from our standard cash adjustment which conservatively adjusts by cash share observed six months prior to ensure the cash balance for the firm is known to the investor.

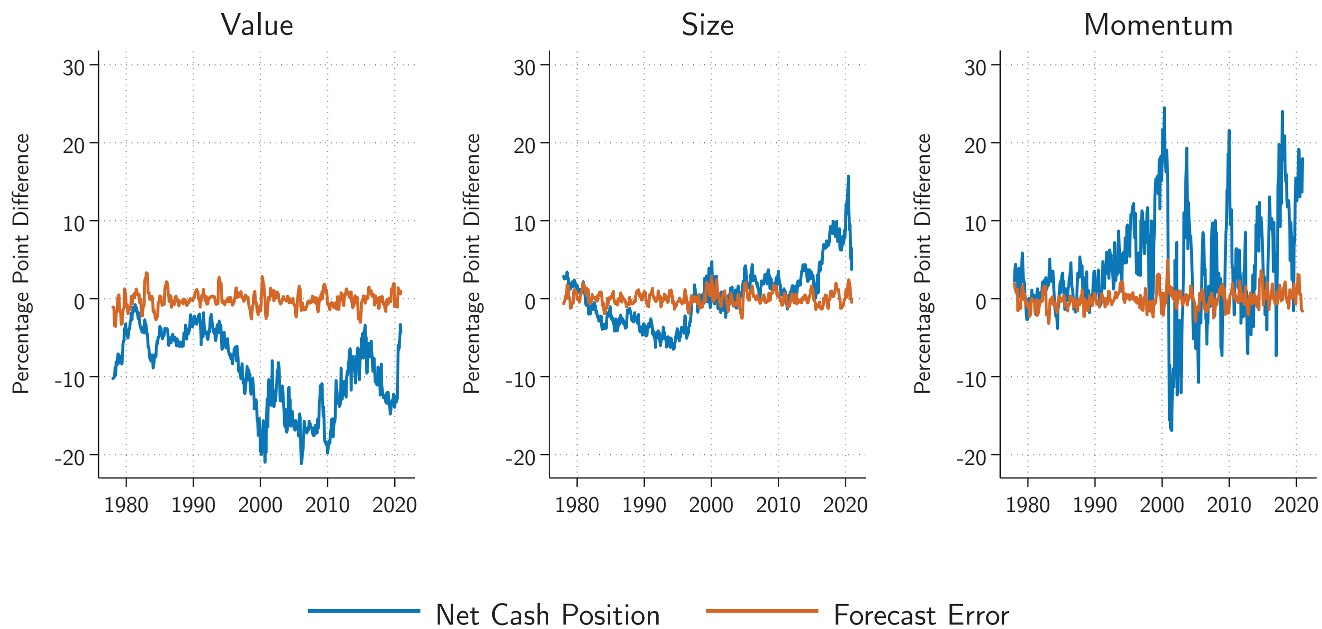


Figure 3.6: Net Cash Holdings. This figure reports the time series of net cash holdings for cash-hedged factor portfolios. We estimate the cash position in each factor's long and short legs. Then, build the factor portfolio as long the cash-adjusted high portfolio and short the cash-adjusted low portfolio. The net cash holding in the factor portfolios is due to error in the estimates of each portfolios' cash holdings.

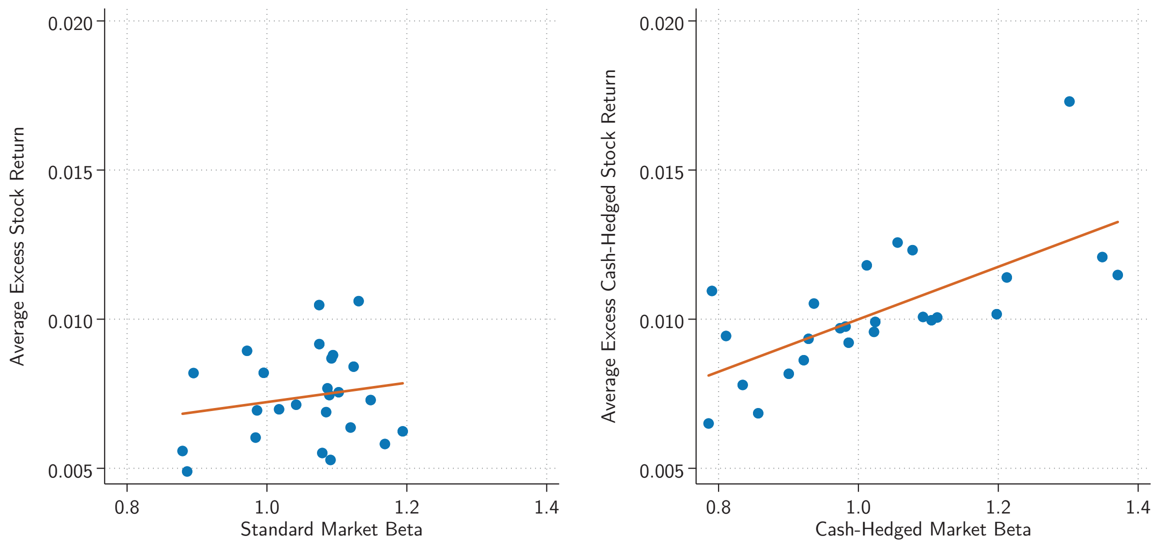


Figure 3.7: Security Market Line for Standard Market and Cash-Hedged Betas for 25 size and book-to-market portfolios. The left panel is the standard common stock security market line using Fama–French's market factor and the Fama–French size/book-to-market 5×5 sorted portfolios. Market beta for each portfolio is the sum of the components of the decomposition shown in Equation 3.16 and equivalent to the coefficient of a time-series regression of the portfolio's return on the market return. The right panel is the security market line for the 25 portfolios using the portfolio's cash-hedged excess returns and cash-hedged beta calculated as the coefficient of a time-series regression of the portfolio's cash-hedged excess return on the market's cash-hedged excess return. To calculate the portfolio's cash-hedged excess return, we calculate each stock's cash-hedged return as the return after adjusting for cash share and then aggregate individual firm cash-hedged returns to the portfolio and market level. The right panel shows the line of best fit for all 25 portfolios.

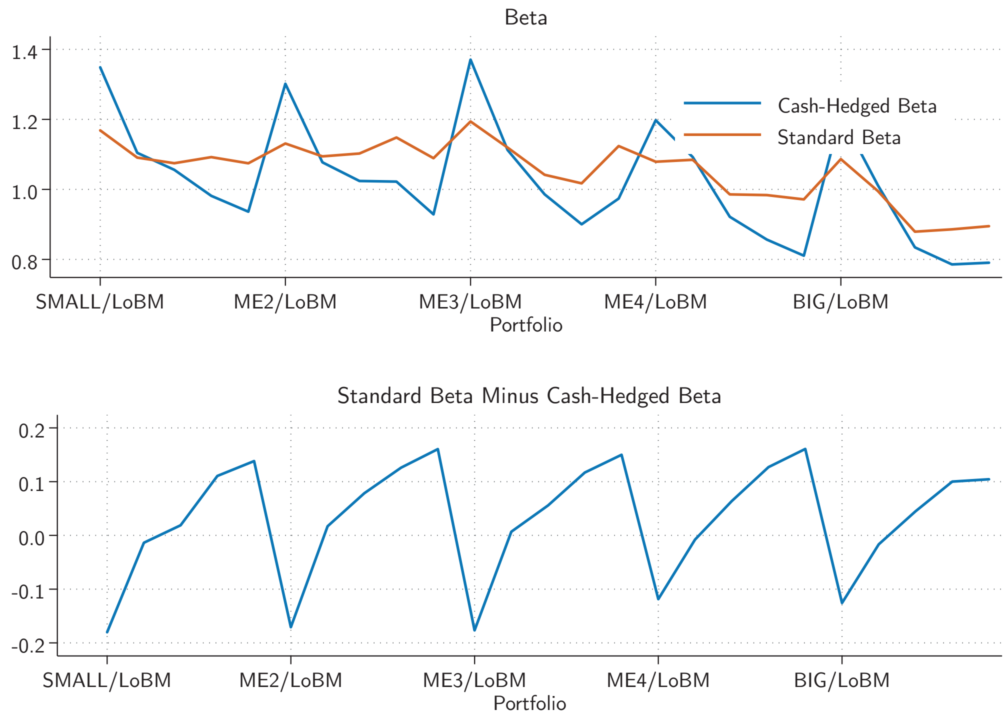


Figure 3.8: CAPM Beta Comparison. The top panel plots the standard beta and cash-hedged beta across the 25 size/book-to-market sorted portfolios. The common beta is calculated from the beta of the 25 portfolios and excess market factor on French's website. The cash-hedged market beta is calculated as described in the beta decomposition discussion, using cash-hedged returns calculated for both the market and the 25 size/book-to-market sorted portfolios.

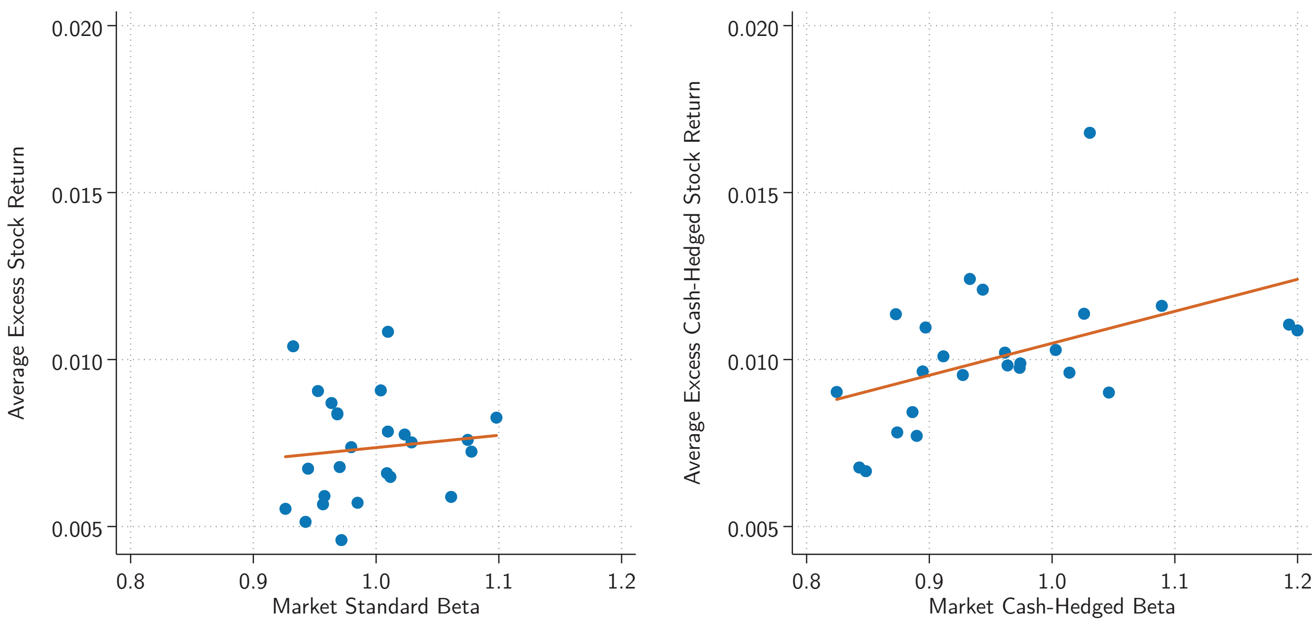


Figure 3.9: Security Market Line for Market from the Fama–French 3 Factor Model for 25 size and book-to-market portfolios. The left panel plots the standard excess returns for the 25 Fama–French size/book-to-market sorted portfolios against that portfolio's market beta from a time-series regression of the Fama–French 3 Factor model. The right panel plots the 25 portfolios' cash-hedged excess returns and cash-hedged market beta calculated using Equation 3.17. To calculate the portfolio's cash-hedged excess return, we calculate each stock's cash-hedged return as the return after adjusting for cash share and then aggregate individual firm cash-hedged returns to the portfolio and market level. The right panel shows the line of best fit for all 25 portfolios.

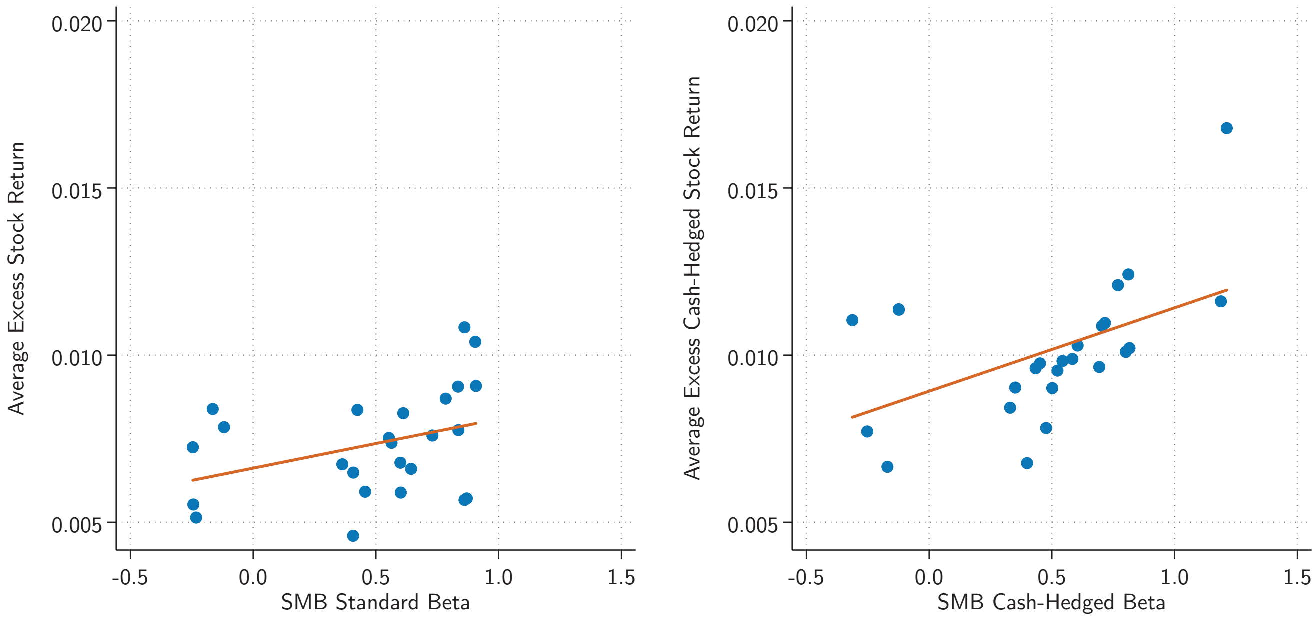


Figure 3.10: Expected Excess Returns and *SMB* Betas from the Fama–French 3 Factor Model for 25 size and book-to-market portfolios. The left panel plots the standard excess returns for the 25 Fama–French size/book-to-market sorted portfolios against that portfolio's *SMB* beta from a time-series regression of the Fama–French 3 Factor model. The right panel plots the 25 portfolios' cash-hedged excess returns and cash-hedged *SMB* beta calculated using Equation 3.17. To calculate the portfolio's cash-hedged excess return, we calculate each stock's cash-hedged return as the return after adjusting for cash share and then aggregate individual firm cash-hedged returns to the portfolio and market level. The right panel shows the line of best fit for all 25 portfolios.

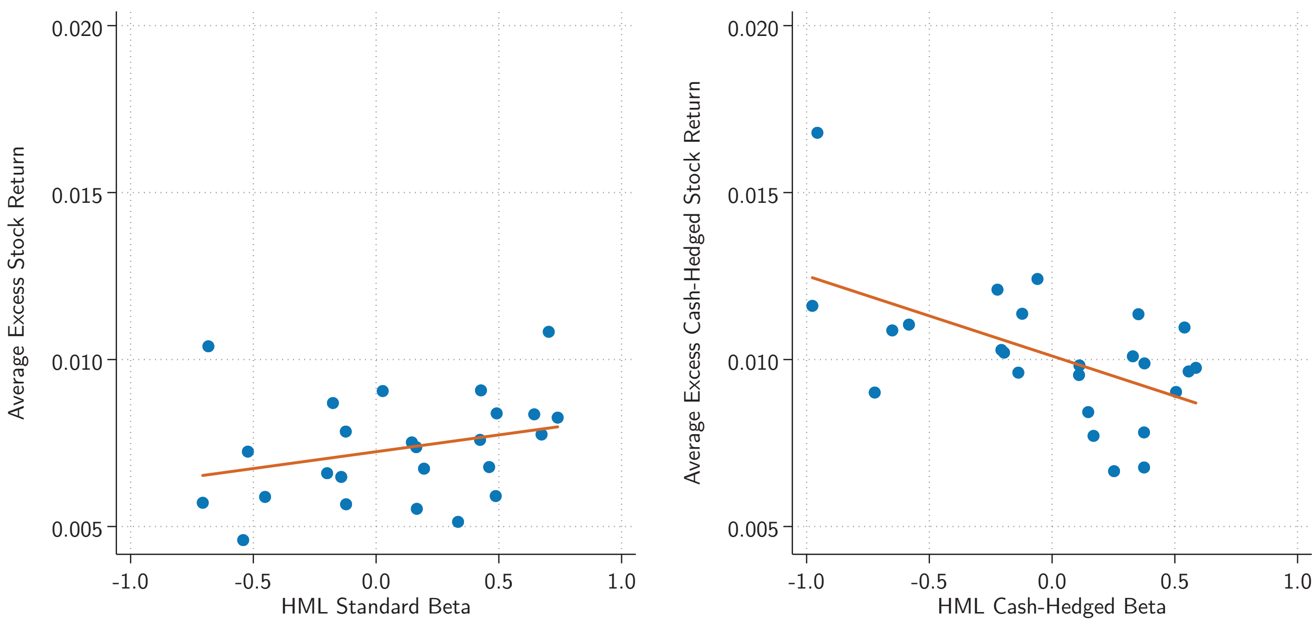


Figure 3.11: Expected Excess Returns and *HML* Betas from the Fama–French 3 Factor Model for 25 size and book-to-market portfolios. The left panel plots the standard excess returns for the 25 Fama–French size/book-to-market sorted portfolios against that portfolio's *HML* beta from a time-series regression of the Fama–French 3 Factor model. The right panel plots the 25 portfolios' cash-hedged excess returns and cash-hedged *HML* beta calculated using Equation 3.17. To calculate the portfolio's cash-hedged excess return, we calculate each stock's cash-hedged return as the return after adjusting for cash share and then aggregate individual firm cash-hedged returns to the portfolio and market level. The right panel shows the line of best fit for all 25 portfolios.

Figure 3.12: Stock and Cash-Hedged Beta from 3 Factor Model. Standard betas are standard betas from Fama–French 3 factor model. Cash-hedged betas are calculated as described in Section 3.5.6.

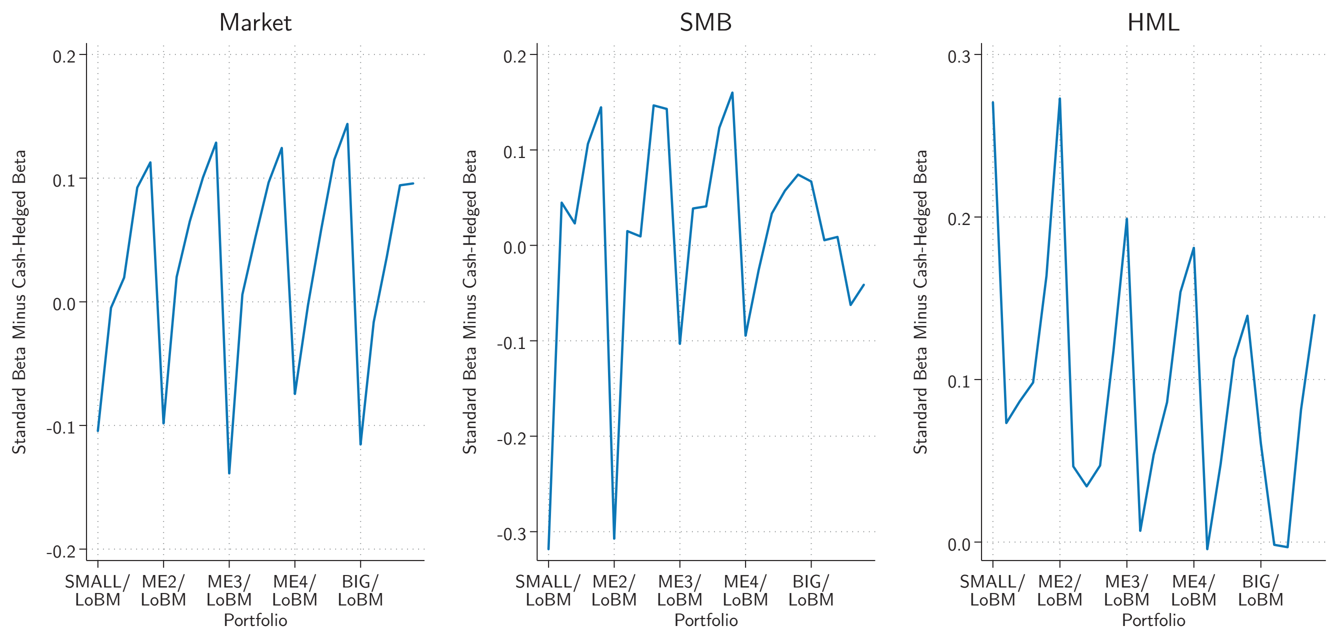


Figure 3.13: Stock and Cash-Hedged Beta Comparison from 3 Factor Model. Plot shows the difference between the standard stock beta and the cash-hedged beta for each factor in the Fama–French 3 factor model. Common stock betas are standard betas from Fama–French 3 factor model. Equity betas are calculated as described in Section 3.5.6.

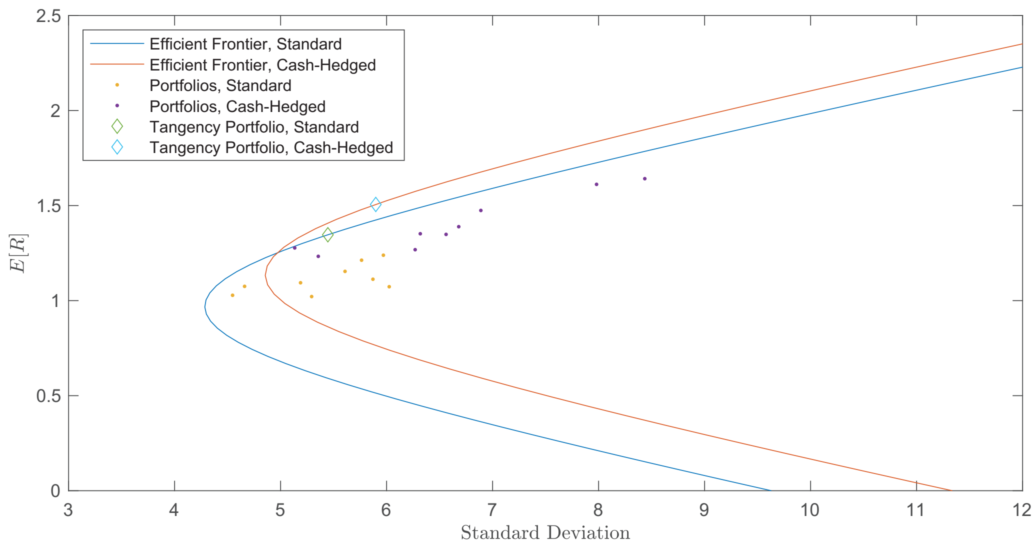


Figure 3.14: Efficient frontier for 9 standard and cash hedged size and book-to-market sorted portfolios. This figure reports the efficient frontier calculated using 9 size and book-to-market sorted portfolios. The two efficient frontiers are calculated using different return data: the standard efficient frontier uses the unhedged stock return portfolios. The cash-hedged efficient frontier uses the cash-hedged stock returns calculated for each of the 9 portfolios. This latter measure of returns uses the cash balance known to investors at the time to hedge out the portfolio's implicit cash holdings. Time frame is January 1980 to December 2020.

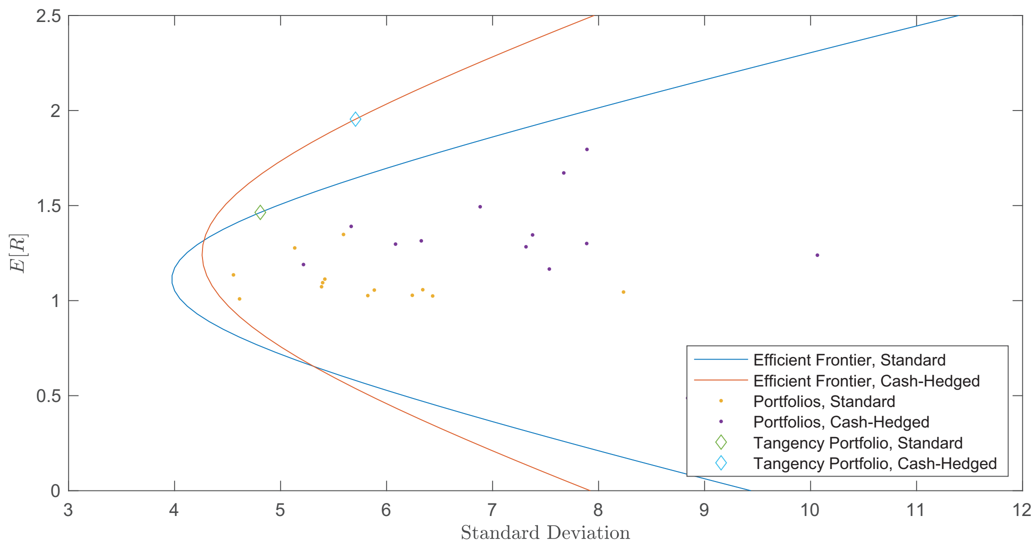


Figure 3.15: Efficient frontier for standard and cash hedged first-letter-of-ticker-symbol sorted portfolios. This figure reports the efficient frontier calculated based on the first letter of the firms' ticker symbols. The two efficient frontiers are calculated using different return data: the standard efficient frontier uses the standard common return on the portfolios. The cash-hedged efficient frontier uses the cash-hedged equity returns calculated for each of the 26 portfolios. This latter measure of returns uses the cash balance known to investors at the time to hedge out the portfolio's implicit cash holdings. Time frame is January 1980 to December 2020.

3.8 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 3.1: Summary of return decompositions.

Book-to-market

	Stock Returns				Non-Cash Component				Cash Component			
	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1
Mean	0.96	1.00	1.14	0.19	1.01	0.99	1.16	0.16	−0.06	0.02	−0.03	0.03
Stdev	5.08	4.55	4.68	3.17	5.05	4.53	4.66	3.13	0.21	0.25	0.21	0.27
Sharpe	0.65	0.76	0.85	0.20	0.69	0.76	0.86	0.17	−1.00	0.27	−0.51	0.38
Alpha, CAPM	0.26	0.38	0.53	0.27	0.32	0.37	0.55	0.23	−0.06	0.02	−0.03	0.03
t-stat	2.86	4.33	5.26	1.69	3.60	4.24	5.40	1.49	−2.65	0.65	−1.51	0.86

Size

	Stock Returns				Non-Cash Component				Cash Component			
	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1
Mean	1.14	1.10	1.01	−0.13	1.19	1.14	1.03	−0.16	−0.11	−0.05	−0.01	0.10
Stdev	5.57	5.31	4.48	2.71	5.53	5.27	4.46	2.73	0.86	0.20	0.13	0.85
Sharpe	0.71	0.72	0.78	−0.16	0.75	0.75	0.80	−0.21	−0.45	−0.93	−0.34	0.40
Alpha, CAPM	0.41	0.38	0.37	−0.03	0.47	0.43	0.39	−0.07	−0.11	−0.06	−0.01	0.10
t-stat	2.95	3.40	7.44	−0.21	2.99	3.73	8.18	−0.44	−1.31	−2.80	−0.93	1.16

Momentum

	Stock Returns				Non-Cash Component				Cash Component			
	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1
Mean	0.93	0.98	1.25	0.32	1.00	1.00	1.23	0.22	−0.07	−0.03	0.02	0.09
Stdev	5.27	4.33	5.54	4.78	5.25	4.33	5.48	4.70	0.15	0.17	0.21	0.23
Sharpe	0.61	0.78	0.78	0.23	0.66	0.80	0.77	0.17	−1.64	−0.57	0.30	1.37
Alpha, CAPM	0.27	0.38	0.55	0.28	0.34	0.41	0.53	0.19	−0.08	−0.03	0.02	0.09
t-stat	2.40	6.24	4.57	1.42	3.19	6.53	4.53	0.97	−4.60	−1.73	1.03	4.04

Cash-to-total assets

	Stock Returns				Non-Cash Component				Cash Component			
	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1
Mean	0.90	1.02	1.21	0.30	0.90	1.01	1.30	0.40	0.01	0.01	−0.10	−0.10
Stdev	4.39	4.36	5.84	3.90	4.39	4.36	5.75	3.78	0.03	0.17	0.32	0.31
Sharpe	0.71	0.81	0.72	0.27	0.71	0.80	0.78	0.37	0.66	0.26	−1.07	−1.15
Alpha, CAPM	0.33	0.42	0.43	0.10	0.32	0.41	0.53	0.20	0.00	0.01	−0.10	−0.10
t-stat	3.23	5.96	3.47	0.52	3.16	5.77	4.80	1.10	1.72	0.68	−2.95	−3.12

Table 3.2: Decomposition of Portfolio Returns into Non-cash and Cash Components. Table reports the returns of value-weighted portfolios formed from sorting stocks into terciles on the book-to-market, size, momentum, and cash-to-total assets. Returns are monthly and reported in percentage points. The table reports returns for value-weighted portfolios of stock returns as well as the stock portfolios returns decomposed into portfolios their non-cash and cash returns. The return of each non-cash portfolio p is defined by the equation $r_t^p = \sum_{i \in p} v_t^i (1 - w_t^i) e_t^i$. The return of each cash portfolio p is defined by the equation $r_t^p = \sum_{i \in p} v_t^i w_t^i b_t^i$. The variable v_t^i is each firm's value weight, w_t^i is a firm's ratio of cash to total assets, e_t^i is a firm's non-cash return, and b_t^i is a firm's cash return. The "Alpha, CAPM" row reports a portfolio's alpha from a time series regression of the portfolio's return on the market return. The *t*-stat column contains *t*-stats for the alphas reported in the above column. *t*-statistics are computed with Newey-West standard errors and ten lags.

Book-to-Market Portfolios								
	Non-Cash Portfolio Return				Cash Portfolio Return			
	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1
Mean	1.31	1.20	1.30	0.00	−0.38	0.37	0.13	0.51
Stdev	6.68	5.24	5.05	4.23	1.28	2.26	2.60	2.52
Sharpe	0.68	0.79	0.89	0.00	−1.03	0.56	0.17	0.70
Alpha, CAPM	0.41	0.49	0.64	0.23	−0.38	0.33	0.09	0.47
t-stat	3.19	4.91	5.86	1.14	−2.91	1.28	0.31	1.66

Size Portfolios								
	Non-Cash Portfolio Return				Cash Portfolio Return			
	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1
Mean	1.40	1.40	1.25	−0.15	−0.54	0.17	0.05	0.59
Stdev	6.64	6.37	5.46	3.34	3.91	1.78	1.53	3.73
Sharpe	0.73	0.76	0.80	−0.15	−0.48	0.33	0.11	0.55
Alpha, CAPM	0.54	0.54	0.48	−0.05	−0.58	0.15	0.03	0.61
t-stat	3.00	4.13	7.46	−0.25	−1.58	0.87	0.18	1.86

Momentum Portfolios								
	Non-Cash Portfolio Return				Cash Portfolio Return			
	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1
Mean	1.18	1.16	1.60	0.42	−0.56	0.16	0.43	0.99
Stdev	6.33	5.06	7.07	6.21	1.95	1.49	1.99	2.26
Sharpe	0.64	0.79	0.78	0.23	−0.99	0.37	0.74	1.51
Alpha, CAPM	0.39	0.47	0.72	0.34	−0.58	0.14	0.41	0.99
t-stat	3.21	6.13	4.58	1.38	−2.77	1.00	1.99	3.88

Cash Share Portfolios								
	Non-Cash Portfolio Return				Cash Portfolio Return			
	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1
Mean	0.92	1.08	1.91	1.00	0.14	0.18	−0.31	−0.46
Stdev	4.46	4.65	8.69	6.42	1.84	2.22	1.55	2.06
Sharpe	0.71	0.80	0.76	0.54	0.27	0.28	−0.70	−0.77
Alpha, CAPM	0.33	0.44	0.79	0.46	0.12	0.16	−0.32	−0.44
t-stat	3.17	5.78	4.32	1.75	0.56	0.70	−1.95	−1.76

Table 3.3: Non-cash and Cash Portfolio Returns for Single-Sorted Portfolios. The non-cash return for portfolio p equals $\sum_{i \in p} v_t^i e_t^i$. The cash return for portfolio p is $\sum_{i \in p} v_t^i b_t^i$. Note, firms' non-cash and cash returns are not scaled by firms' cash-shares for these portfolios' construction. The "Alpha, CAPM" column reports a portfolio's alpha from a time series regression of the portfolio's return on the market return. The t-stat column contains t-stats for the alphas reported in the above column. t-statistics are computed with Newey-West standard errors and ten lags.

Book-to-Market Portfolios				
	P1	P2	P3	P3-P1
Mean	0.16	0.10	0.07	−0.09
Stdev	0.06	0.04	0.02	0.05

Size Portfolios				
	P1	P2	P3	P3-P1
Mean	0.11	0.11	0.11	0.00
Stdev	0.02	0.03	0.04	0.03

Momentum Portfolios				
	P1	P2	P3	P3-P1
Mean	0.10	0.10	0.14	0.04
Stdev	0.04	0.05	0.06	0.06

Cash Share Portfolios				
	P1	P2	P3	P3-P1
Mean	0.02	0.06	0.25	0.23
Stdev	0.01	0.02	0.08	0.07

Table 3.4: Cash to total asset ratios for tercile portfolio sorts on book-to-market, size, momentum, and cash-to-total assets. The table reports average cash shares for portfolios formed from stocks sorted into terciles on the book-to-market, size, momentum, and cash-to-total assets variables. A firm's cash share is the ratio of its cash to total assets. The cash share of a value-weighted portfolio p in month t is $\sum_{i \in p} v_t^i w_t^i$. The mean column reports the time series average of each portfolios' monthly cash-shares. The standard deviation reports the time series standard deviation of each portfolios' monthly cash-shares.

	Mean	Std. Dev.	Min.	Max.	Sharpe
Market Standard Excess Return	0.76	4.73	−23.16	14.52	0.50
Market Cash-Hedged Excess Return	1.06	5.76	−25.43	20.60	0.58
Market Cash Excess Return	−0.12	1.62	−8.09	8.26	−0.26
Cash Share	11.71	4.38	3.30	23.59	

Table 3.5: Summary statistics. We describe the construction of firm cash-hedged excess returns in section 3.5.2. Briefly, a firm's cash-hedged return is the return of a portfolio long the firm's common stock and short the firm's cash and short-term equivalents. Excess returns are monthly. Cash share is the value-weighted aggregate market cash share. Sharpe ratio is annualized using monthly data.

	(1) Unhedged	(2) Unhedged Market	(3) Unhedged Market (Fama–French)
Cash-Hedged	0.711***		
	(59.26)		
Cash-Hedged Market		0.820***	0.720***
		(106.02)	(28.21)
Constant	0.000**	−0.001***	0.000
	(2.70)	(−4.42)	(0.44)
Observations	217,672	555	555
Adjusted R^2	0.86	0.99	0.86

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.6: Regression of stock excess returns on non-cash excess returns. We describe the construction of firm cash-hedged excess returns in section 3.5.2. Briefly, a firm's cash-hedged return is the return of a portfolio long the firm's common stock and short the firm's cash and short-term equivalents. "Unhedged Market" in Column 2 is the value-weighted aggregate market return of the sample described in Section 3.4. "Unhedged Market (Fama–French)" in Column 3 is the value-weighted aggregate market return as available on Ken French's website. The firm level regression in column includes firm fixed effects and robust standard errors clustered at the firm level.

		Standard		Cash-Hedged	
		Mean	Sharpe	Mean	Sharpe
Simple Factors	*Value*	2.80	0.19	0.45	0.02
	Size	−1.93	−0.18	−1.87	−0.14
	Mom	3.95	0.23	5.41	0.24
	Cash	3.98	0.27	13.40	0.56
Sorts	HML	1.46	0.14	−2.37	−0.16
	HML^{Triple}	2.98	0.32	1.24	0.11
	SMB	1.24	0.14	1.63	0.14
	SMB^{Triple}	0.74	0.09	0.35	0.04
	WML	5.37	0.34	6.17	0.29
	WML^{Triple}	4.22	0.31	3.88	0.23
	$Cash^{Triple}$	5.29	0.47	13.11	0.71
Strategies	$1/2\,HML + 1/2\,WML$	3.25	0.52	1.67	0.19
	$1/2\,HML^{Triple} + 1/2\,WML^{Triple}$	3.60	0.62	2.55	0.35
	$1/3\,HML + 1/3\,WML + 1/3\,CASH$	3.84	0.70	5.77	0.75
	$1/3\,HML^{Triple} + 1/3\,WML^{Triple} + 1/3\,CASH$	4.16	0.78	5.97	0.80

Table 3.7: Sort and factor premia. Annualized returns and sharpe ratios. Simple factors are high tercile minus low tercile (P3−P1), whereas sorts are double or triple sorts to control for covariance with size and cash holdings. E.g., *Cash* refers to the premia earned by the strategy long firms in the top tercile for cash share and short firms in the bottom tercile for cash share. HML^{Triple} is triple sorted to control for covariance between value, size and cash; $Cash^{Triple}$ is tripled sorted to control for covariance between cash holdings, size and cash.

	Book-to-Market Portfolios				
Size	Low	2	3	4	High
Small	0.21	0.15	0.11	0.08	0.07
	0.21	0.14	0.10	0.08	0.06
	0.21	0.13	0.10	0.07	0.06
	0.17	0.13	0.10	0.07	0.05
Big	0.16	0.14	0.10	0.08	0.07

Table 3.8: Average Cash Share for 25 Size/BEME-Sorted Portfolios. For each portfolio, the value-weighed cash share is calculated at each point in time. Table reports the time-series average of the value-weighted cash share.

	(1) Cash Share	(2) Cash Share	(3) Cash Share	(4) Cash Share	(5) Δ(Cash Share)	(6) Δ(Cash Share)	(7) Δ(Cash Share)	(8) Δ(Cash Share)
Size	-0.019			-0.045^{**}				
	(-1.21)			(-2.97)				
Book-to-market		-0.332^{***}		-0.335^{***}				
		(-22.65)		(-21.39)				
Momentum			0.094^{***}	0.002				
			(12.02)	(0.20)				
Δ(Size)					0.075^{***}			0.029^{*}
					(6.44)			(2.04)
Δ(Book-to-market)						-0.088^{***}		-0.063^{***}
						(-7.89)		(-4.25)
Δ(Momentum)							0.024^{***}	0.010^{*}
							(6.64)	(2.22)
Constant	51.329^{***}	67.076^{***}	45.535^{***}	69.374^{***}	-0.570^{***}	-0.412^{***}	-0.461^{***}	-0.440^{***}
	(59.49)	(72.97)	(68.20)	(49.90)	(-8.06)	(-5.82)	(-6.60)	(-6.25)
Observations	17,910	17,910	17,708	17,708	15,437	15,437	15,282	15,282

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.9: Regression of cash share percentile onto characteristic percentiles. Observations are firm-year, as measured by characteristics known in January of each year. We independently sort stocks into percentiles for size, value, momentum and cash share each January, as well as the change in the percentile from the previous January. Percentile on percentile regression (columns 1 through 3) have Newey-West standard errors with ten lags, corresponding to a decade. Difference in percentile on difference in percentile regression are are clustered at the firm level.

	(1) Market	(2) HML	(3) SMB	(4) WML
HML	-0.344^{***}		-0.168^{**}	-0.422^{***}
	(−3.51)		(−2.62)	(−4.01)
SMB	0.329^{***}	-0.155^{**}		0.040
	(3.42)	(−3.17)		(0.36)
WML	-0.205^{***}	-0.177^{***}	0.018	
	(−3.72)	(−4.34)	(0.35)	
MKT		-0.146^{***}	0.152^{***}	-0.208^{**}
		(−3.68)	(4.27)	(−3.24)
Constant	0.008^{***}	0.004^{**}	0.001	0.008^{***}
	(4.08)	(2.76)	(0.47)	(4.26)
Observations	516	516	516	516
Adjusted R^2	0.13	0.14	0.09	0.09

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.10: Spanning Test: Fama–French Factors. Table presents the results from regressing the standard, unhedged Fama–French factors on the remaining factors. Data from Ken French's website. Robust standard errors in parentheses.

	(1) Market	(2) HML	(3) SMB	(4) WML
HML	-0.676^{***}		-0.142^{*}	-0.775^{***}
	(−10.00)		(−2.23)	(−6.33)
SMB	0.256^{*}	-0.142^{*}		−0.154
	(2.41)	(−2.35)		(−1.45)
WML	-0.215^{***}	-0.394^{***}	−0.051	
	(−3.94)	(−7.42)	(−1.11)	
MKT		-0.266^{***}	0.100^{**}	-0.246^{***}
		(−6.11)	(2.63)	(−3.85)
Constant	0.009^{***}	0.002	0.000	0.009^{***}
	(4.00)	(1.60)	(0.16)	(3.89)
Observations	516	516	516	516
Adjusted R^2	0.23	0.47	0.07	0.28

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.11: Spanning Test: Cash-Hedged Factors. Table presents the results from regressing the cash-hedged factors on the remaining cash-hedged factors. Robust standard errors in parentheses.

	(1) Market	(2) HML	(3) SMB	(4) WML	(5) CASH
HML	0.097		-0.183^{**}	-1.125^{***}	-0.903^{***}
	(1.16)		(−2.65)	(−10.65)	(−15.60)
SMB	0.218^{**}	-0.116^{**}		−0.130	−0.065
	(2.64)	(−2.81)		(−1.34)	(−0.90)
WML	−0.019	-0.333^{***}	−0.061		-0.208^{***}
	(−0.39)	(−9.34)	(−1.30)		(−3.86)
CASH	0.626^{***}	-0.411^{***}	−0.047	-0.320^{***}	
	(13.50)	(−9.92)	(−0.88)	(−3.41)	
MKT		0.035	0.123^{**}	−0.023	0.492^{***}
		(1.17)	(2.79)	(−0.39)	(12.43)
Constant	0.003	0.004^{**}	0.000	0.006^{**}	0.005^{**}
	(1.52)	(3.17)	(0.34)	(2.86)	(3.17)
Observations	516	516	516	516	516
Adjusted R^2	0.47	0.67	0.08	0.39	0.66

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.12: Spanning Test: Cash-Hedged Factors with *CASH* Factor. Table presents the results from regressing the cash-hedged factors on the remaining cash-hedged factors. Robust standard errors in parentheses.

	(1) Size	(2) BEME	(3) Mom
Constant	0.342	-9.273^{***}	4.146^{***}
	(0.59)	(-12.28)	(5.18)
Observations	516	516	538

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.13: Net Cash Holding Is Statistically Non-zero for Value and Momentum. Table shows result from regressing net cash holding shown in Figure 3.5 – the cash holding of the long leg minus the cash holding of the short leg, in percentage points – on a constant. Newey-West standard errors with 12 lags.

	(1) Size	(2) BEME	(3) Mom
Constant	0.061	−0.177	−0.025
	(0.81)	(−1.88)	(−0.26)
Observations	516	516	516

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.14: Net Cash Holding is Statistically Zero in Cash-Hedged Factors. Table shows result from regressing net cash holding of the cash hedged portfolios (equivalently, the forecast errors shown in Figure 3.6) on a constant. Newey-West standard errors with 12 lags.

Size	BE/ME	β^p	$=$	$\beta^{p,cash-hedged}$	$\times$	$\frac{\text{Var}(e_t^{m,xs})}{\text{Var}(r_t^{m,xs})}$	$+$	$\frac{-\text{Cov}(\gamma_t^p, e_t^{m,xs})}{\text{Var}(r_t^{m,xs})}$	$\frac{-\text{Cov}(e_t^{p,xs}, \gamma_t^m)}{\text{Var}(r_t^{m,xs})}$	$\frac{\text{Cov}(\gamma_t^p, \gamma_t^m)}{\text{Var}(r_t^{m,xs})}$
Small	Lo	1.17		1.35		1.51		-0.59	-0.41	0.13
	2	1.09		1.10		1.51		-0.35	-0.31	0.07
	3	1.07		1.06		1.51		-0.29	-0.30	0.07
	4	1.09		0.98		1.51		-0.17	-0.26	0.03
	Hi	1.07		0.94		1.51		-0.12	-0.25	0.02
ME2	Lo	1.13		1.30		1.51		-0.57	-0.40	0.13
	2	1.09		1.08		1.51		-0.29	-0.30	0.06
	3	1.10		1.02		1.51		-0.21	-0.28	0.04
	4	1.15		1.02		1.51		-0.15	-0.28	0.03
	Hi	1.09		0.93		1.51		-0.10	-0.23	0.02
ME3	Lo	1.19		1.37		1.51		-0.61	-0.40	0.14
	2	1.12		1.11		1.51		-0.31	-0.32	0.07
	3	1.04		0.99		1.51		-0.23	-0.27	0.05
	4	1.02		0.90		1.51		-0.14	-0.23	0.03
	Hi	1.12		0.97		1.51		-0.12	-0.25	0.02
ME4	Lo	1.08		1.20		1.51		-0.49	-0.36	0.11
	2	1.08		1.09		1.51		-0.33	-0.31	0.07
	3	0.99		0.92		1.51		-0.21	-0.24	0.05
	4	0.98		0.86		1.51		-0.12	-0.21	0.02
	Hi	0.97		0.81		1.51		-0.07	-0.20	0.01
BIG	Lo	1.09		1.21		1.51		-0.48	-0.39	0.12
	2	1.00		1.01		1.51		-0.31	-0.29	0.07
	3	0.88		0.83		1.51		-0.20	-0.22	0.05
	4	0.89		0.79		1.51		-0.12	-0.20	0.03
	Hi	0.90		0.79		1.51		-0.12	-0.20	0.03
Average		1.06		1.03		1.51		-0.27	-0.28	0.06

Table 3.15: Beta Decomposition for 25 Size and Book-to-Market Sorted Portfolios. The beta for each portfolio is decomposed into the cash-hedged beta, ratio of variances, and drag terms as defined in Equation 3.16.

Size	BE/ME	$\beta^{p,Mkt,3factor}$	$=$	$\beta^{p,Mkt,cash-hedged,3factor}$	$\times$	$\frac{var(\tilde{e}_t^{Mkt})}{var(\tilde{r}_t^{Mkt})}$	$+$	$\frac{-cov(\tilde{\gamma}_t^p,\tilde{e}_t^{Mkt})}{var(\tilde{r}_t^{Mkt})}$	$+$	$\frac{-cov(\tilde{e}_t^{p,xs},\tilde{\gamma}_t^{Mkt})}{var(\tilde{r}_t^{Mkt})}$	$+$	$\frac{cov(\tilde{\gamma}_t^p,\tilde{\gamma}_t^{Mkt})}{var(\tilde{r}_t^{Mkt})}$
Small	Lo	0.98		1.09		1.49		-0.43		-0.30		0.09
	2	0.96		0.96		1.49		-0.29		-0.25		0.06
	3	0.95		0.93		1.49		-0.24		-0.25		0.06
	4	1.00		0.91		1.49		-0.15		-0.24		0.03
	Hi	1.01		0.90		1.49		-0.10		-0.25		0.02
ME2	Lo	0.93		1.03		1.49		-0.41		-0.29		0.09
	2	0.96		0.94		1.49		-0.25		-0.25		0.05
	3	1.03		0.96		1.49		-0.19		-0.25		0.04
	4	1.07		0.97		1.49		-0.14		-0.27		0.03
	Hi	1.02		0.89		1.49		-0.10		-0.23		0.02
ME3	Lo	1.06		1.20		1.49		-0.51		-0.33		0.11
	2	1.01		1.00		1.49		-0.28		-0.27		0.06
	3	0.98		0.93		1.49		-0.20		-0.25		0.04
	4	0.97		0.87		1.49		-0.13		-0.23		0.03
	Hi	1.10		0.97		1.49		-0.12		-0.26		0.03
ME4	Lo	0.97		1.05		1.49		-0.39		-0.28		0.09
	2	1.01		1.01		1.49		-0.29		-0.28		0.07
	3	0.94		0.89		1.49		-0.19		-0.23		0.04
	4	0.96		0.84		1.49		-0.11		-0.21		0.02
	Hi	0.97		0.82		1.49		-0.06		-0.21		0.01
BIG	Lo	1.08		1.19		1.49		-0.46		-0.35		0.11
	2	1.01		1.03		1.49		-0.31		-0.28		0.07
	3	0.93		0.89		1.49		-0.22		-0.23		0.05
	4	0.94		0.85		1.49		-0.13		-0.22		0.03
	Hi	0.97		0.87		1.49		-0.13		-0.23		0.03
Average		0.99		0.96		1.49		-0.23		-0.26		0.05

Table 3.16: Decomposition of Market Beta from the Fama–French 3 Factor Regression for 25 Size and Book-to-Market Sorted Portfolios. The market beta for each portfolio is decomposed into the cash-hedged market beta, ratio of variances, and an adjustment term, defined analogously to Equation 3.17.

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	0.87	1.19	1.64	-0.81	-0.59	0.33
	2	0.86	0.82	1.64	-0.29	-0.28	0.10
	3	0.83	0.81	1.64	-0.27	-0.32	0.09
	4	0.91	0.80	1.64	-0.20	-0.28	0.08
	Hi	0.86	0.72	1.64	-0.15	-0.23	0.06
ME2	Lo	0.90	1.21	1.64	-0.82	-0.59	0.32
	2	0.78	0.77	1.64	-0.27	-0.30	0.09
	3	0.55	0.54	1.64	-0.16	-0.25	0.07
	4	0.73	0.58	1.64	-0.11	-0.14	0.03
	Hi	0.84	0.69	1.64	-0.11	-0.23	0.04
ME3	Lo	0.60	0.70	1.64	-0.41	-0.28	0.14
	2	0.64	0.60	1.64	-0.20	-0.19	0.05
	3	0.56	0.52	1.64	-0.18	-0.17	0.06
	4	0.60	0.48	1.64	-0.07	-0.12	0.01
	Hi	0.61	0.45	1.64	-0.04	-0.09	0.00
ME4	Lo	0.41	0.50	1.64	-0.31	-0.21	0.11
	2	0.41	0.43	1.64	-0.19	-0.15	0.04
	3	0.36	0.33	1.64	-0.11	-0.09	0.03
	4	0.46	0.40	1.64	-0.09	-0.13	0.03
	Hi	0.42	0.35	1.66	-0.04	-0.12	0.00
BIG	Lo	-0.25	-0.31	1.64	0.15	0.19	-0.07
	2	-0.12	-0.12	1.64	0.06	0.07	-0.04
	3	-0.24	-0.25	1.64	0.10	0.12	-0.06
	4	-0.23	-0.17	1.64	0.05	0.02	-0.02
	Hi	-0.16	-0.12	1.64	0.08	0.00	-0.04
Average		0.49	0.48	1.64	-0.18	-0.17	0.06

Table 3.17: Decomposition of SMB Beta from the Fama–French 3 Factor Regression for 25 Size and Book-to-Market Sorted Portfolios. The SMB beta for each portfolio is decomposed into the cash-hedged SMB beta, ratio of variances, and an adjustment term, defined analogously to Equation 3.17.

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	-0.71	-0.98	1.75	0.77	0.53	-0.30
	2	-0.12	-0.20	1.75	0.23	0.07	-0.08
	3	0.03	-0.06	1.75	0.15	0.04	-0.06
	4	0.43	0.33	1.75	-0.02	-0.12	-0.01
	Hi	0.70	0.54	1.75	-0.06	-0.21	0.03
ME2	Lo	-0.68	-0.96	1.75	0.76	0.53	-0.30
	2	-0.18	-0.22	1.75	0.18	0.12	-0.08
	3	0.15	0.11	1.75	-0.01	-0.03	-0.01
	4	0.42	0.38	1.75	-0.09	-0.16	0.02
	Hi	0.67	0.56	1.75	-0.09	-0.22	0.01
ME3	Lo	-0.45	-0.65	1.75	0.55	0.42	-0.28
	2	-0.20	-0.21	1.75	0.12	0.11	-0.07
	3	0.16	0.11	1.75	0.04	-0.04	-0.03
	4	0.46	0.37	1.75	-0.05	-0.15	0.01
	Hi	0.74	0.59	1.75	-0.06	-0.24	0.01
ME4	Lo	-0.54	-0.72	1.75	0.58	0.36	-0.22
	2	-0.14	-0.14	1.75	0.09	0.06	-0.05
	3	0.20	0.15	1.75	0.03	-0.07	-0.03
	4	0.49	0.37	1.75	0.00	-0.16	-0.01
	Hi	0.64	0.51	1.74	-0.05	-0.20	0.01
BIG	Lo	-0.52	-0.58	1.75	0.35	0.28	-0.14
	2	-0.12	-0.12	1.75	0.06	0.07	-0.04
	3	0.17	0.17	1.75	-0.04	-0.10	0.00
	4	0.33	0.25	1.75	-0.03	-0.09	0.01
	Hi	0.49	0.35	1.75	-0.05	-0.10	0.02
Average		0.10	0.00	1.75	0.14	0.03	-0.06

Table 3.18: Decomposition of HML Beta from the Fama–French 3 Factor Regression for 25 Size and Book-to-Market Sorted Portfolios. The HML beta for each portfolio is decomposed into the cash-hedged HML beta, ratio of variances, and an adjustment term, defined in Equation 3.17.

9 Size/Book-to-Market Sorted Portfolios	R_{tan}	σ_{tan}	r_f	Sharpe
Standard	1.34	5.45	0.36	0.63
Cash Hedged	1.51	5.90	0.36	0.68
First Letter of Ticker Portfolios	R_{tan}	σ_{tan}	r_f	Sharpe
Standard	1.46	4.80	0.36	0.80
Cash Hedged	1.95	5.70	0.36	0.97

Table 3.19: Tangency Portfolio Summary Statistics. Table reports the monthly moments of the tangency portfolio as calculated from the efficient frontier shown in Figures 3.14 and 3.15. Cash hedged portfolios contain the same stocks as the standard portfolios, but their returns are equity returns and hedged to compensate for the portfolio's implicit cash holdings. Sharpe ratio annualized from monthly statistics.

Prices of Risk: $\mathbb{E}[R_i^e] = \alpha + \beta'\lambda$				
MODEL	CAPM		4 Factor	
	Standard	Hedged	Standard	Hedged
Intercept	0.099	−0.057	−0.053	0.191
t-GMM	(0.23)	−0.114	(−0.13)	(0.43)
t-FM	(0.24)	(−0.12)	(−0.14)	(0.45)
Mkt−R_f	0.631	1.081	0.774	0.824
t-GMM	(1.31)	(1.94)	(1.67)	(1.58)
t-FM	(1.34)	(2.06)	(1.74)	(1.64)
HML			0.054	−0.298
t-GMM			(0.38)	(−1.48)
t-FM			(0.38)	(−1.49)
SMB			0.099	0.159
t-GMM			(0.85)	(1.05)
t-FM			(0.85)	(1.05)
WML			0.347	0.468
t-GMM			(1.64)	(1.68)
t-FM			(1.66)	(1.69)
Diagnostics				
MAPE (%)	0.14	0.14	0.12	0.12
Mean TS R^2	0.72	0.68	0.84	0.81
GRS p-value	0.00	0.30	0.01	0.44
Annualized Risk Premium	0.73	2.16	0.55	0.72
Months (T)	515	515	515	515
Portfolios (N)	35	35	35	35

Table 3.20: Pricing 25 Size/Book-to-Market Portfolios. Table presents the pricing results for the 25 size and book-to-market and 10 momentum-sorted portfolios. Coefficient presents the price of risk, λ_{fac}. Unhedged columns present the results from a model using common excess returns for both factors and portfolios: that is, returns for the factors and portfolios that have not been adjusted for cash holdings. Hedged columns refers to tests in which both the factors and portfolios have been adjusted to hedge out the implicit cash holdings. Standard and hedged factors and portfolios are those as described in the data construction section. All returns are excess returns. Fama-MacBeth t-stats. MAPE is mean absolute pricing error. T.S. R^2 is the average time series R^2. GRS is the Gibbons-Ross-Shaken test whether the pricing errors are jointly zero. Annualized risk premium row is the increase in expected return associated with a 1 standard deviation increase in β_{Mkt}: $\sigma^\beta \times \lambda^{Mkt}$.

Standard Returns						
Average Return	Low	Book-to-Market			High	Average
Small	0.58	0.53	0.92	0.87	1.05	0.79
	1.06	0.88	0.76	0.73	0.75	0.83
	0.62	0.64	0.71	0.70	0.84	0.70
	0.55	0.69	0.69	0.60	0.89	0.69
Big	0.77	0.82	0.56	0.49	0.82	0.69
Average	0.72	0.71	0.73	0.68	0.87	
Standard Deviation						
	7.09	6.17	5.91	6.17	6.28	6.33
	6.86	6.01	6.00	6.22	6.35	6.29
	6.64	5.98	5.58	5.81	6.48	6.09
	5.94	5.67	5.26	5.52	5.63	5.60
Big	5.70	5.19	4.73	4.79	5.05	5.09
Average	6.44	5.80	5.50	5.70	5.96	
CAPM Pricing Errors						
Small	−0.27	−0.26	0.13	0.07	0.26	−0.01
	0.23	0.09	−0.05	−0.12	−0.06	0.02
	−0.25	−0.18	−0.04	−0.04	0.01	−0.10
	−0.23	−0.10	−0.03	−0.11	0.18	−0.06
Big	−0.02	0.10	−0.08	−0.15	0.17	0.00
Average	−0.11	−0.07	−0.01	−0.07	0.11	

Cash-Hedged Returns						
Average Return	Low	Book-to-Market			High	Average
Small	1.21	1.00	1.26	0.98	1.05	1.10
	1.73	1.23	0.99	0.96	0.93	1.17
	1.15	1.01	0.92	0.82	0.97	0.97
	1.02	1.01	0.86	0.68	0.94	0.90
Big	1.14	1.18	0.78	0.65	1.09	0.97
Average	1.25	1.08	0.96	0.82	1.00	
Standard Deviation						
	10.81	7.93	7.35	7.04	6.95	8.02
	10.48	7.48	7.07	7.01	6.91	7.79
	9.77	7.49	6.65	6.44	7.02	7.47
	8.37	7.19	6.14	6.11	5.98	6.76
Big	7.79	6.57	5.69	5.31	5.57	6.19
Average	9.44	7.33	6.58	6.38	6.49	
CAPM Pricing Errors						
Small	−0.17	−0.12	0.18	−0.02	0.09	−0.01
	0.40	0.14	−0.05	−0.09	−0.02	0.07
	−0.25	−0.13	−0.08	−0.10	−0.03	−0.12
	−0.20	−0.10	−0.08	−0.19	0.11	−0.09
Big	−0.10	0.16	−0.06	−0.14	0.29	0.03
Average	−0.06	−0.01	−0.02	−0.11	0.09	

Table 3.21: Summary Statistics and Pricing Errors 25 Size and Book-to-Market Portfolios Under Standard CAPM and Cash-Hedged CAPM. Table presents the average returns in terms of both common returns and equity returns, where equity returns hedge out the cash holdings known to investors. Common CAPM pricing errors are the time-series pricing errors across all 25 portfolios using the aggregate stock market excess return as the single factor across the 25 Fama-French size and book-to-market portfolios, both available from Ken French's website. Equity CAPM pricing errors are the time-series pricing errors across all 25 portfolios using cash adjusted returns in the sample described in the data section, and the market factor is similarly cash hedged. All returns are excess returns.

	Equity Return		Cash-Hedged Return		Cash Return	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.987	1.552	0.892	1.424	-0.138	-5.559
	(4.69)	(2.17)	(4.44)	(1.75)	(-0.98)	(-3.85)
Cash Share	1.289	1.676	4.975	5.363	-3.069	-2.164
	(2.04)	(2.58)	(4.31)	(4.63)	(-2.80)	(-1.87)
ln(Size)		-0.034		-0.035		0.358
		(-0.87)		(-0.74)		(4.30)
ln(B/M)		0.212		0.200		0.416
		(2.74)		(2.24)		(3.12)
Months (T)	548	548	548	548	548	548
Firms (N)	1855	1855	1855	1855	1855	1855

Table 3.22: Cross-sectional Regression of Firm Returns Using Cash Share. Table presents the cross-sectional pricing results for monthly firm returns. The regressions test the relationship between a firms' cash shares and expected returns for equity, cash-hedged, and cash returns. Coefficients are the price of risk estimates, and Fama–MacBeth t-statistics are reported.

3.9 Appendix

	$r_{i,t} - R^B_{i,t}$
ΔC_t	1.261***
	(0.032)
ΔE_t	0.737***
	(0.015)
ΔNA_t	0.219***
	(0.007)
ΔRD_t	1.124***
	(0.142)
ΔI_t	−1.598***
	(0.113)
ΔD_t	2.530***
	(0.231)
C_{t-1}	0.156***
	(0.008)
L_t	−0.293***
	(0.006)
NF_t	−0.081***
	(0.013)
$C_{t-1} \times \Delta C_t$	−0.719***
	(0.064)
$L_t \times \Delta C_t$	−1.171***
	(0.068)
Constant	0.010***
	(0.002)
Observations	81,289
Adjusted R^2	0.16

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.23: 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 (1992b) 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

Bibliography

Viral Acharya, Sergei A Davydenko, and Ilya A Strebulaev. Cash holdings and credit risk. *The Review of Financial Studies*, 25(12):3572–3609, 2012.

Viral V. Acharya, Heitor Almeida, and Murillo Campello. Is cash negative debt? a hedging perspective on corporate financial policies. *Journal of Financial Intermediation*, 16(4):515 – 554, 2007.

Viral V. Acharya, Matteo Crosignani, Tim Eisert, and Christian Eufinger. Zombie Credit and (Dis-)Inflation: Evidence from Europe. 2020.

Tobias Adrian, Erkko Etula, and Tyler Muir. Financial Intermediaries and the Cross-Section of Asset Returns. *Journal of Finance*, 2014.

Andrew W. Alford, Jennifer J. Jones, and Mark E. Zmijewski. Extensions and violations of the statutory sec form 10-k filing requirements. *Journal of Accounting and Economics*, 17(1):229 – 254, 1994. ISSN 0165-4101.

Heitor Almeida, Murillo Campello, and Michael S. Weisbach. The cash flow sensitivity of cash. *The Journal of Finance*, 59(4):1777–1804, 2004.

Dan Andrews, Muge A. McGowan, and Valentine Millot. The Walking Dead? Zombie Firms and Productivity Performance in OECD Countries. *OECD Working Paper No. 1372*, 2017.

Clifford Asness. *Variables that explain stock returns*. PhD thesis, University of Chicago, 1994.

Clifford S. Asness. Momentum in Japan: The Exception that Proves the Rule. *Journal of Portfolio Management*, 37(4):67–75, 2011.

Clifford S. Asness, Tobias J. Moskowitz, and Lasse H. Pedersen. Value and Momentum Everywhere. *Journal of Finance*, 2013a.

Cliford S. Asness, Tobias J. Moskowitz, and Lasse Heje Pedersen. Value and Momentum Everywhere. *Journal of Finance*, 2013b.

Ryan Banerjee and Boris Hofmann. The rise of zombie firms: causes and consequences. *BIS Quarterly Review*, pages 67–78, 2018.

Thomas W. Bates, Kathleen M. Kahle, and René M. Stulz. Why do u.s. firms hold so much more cash than they used to? *The Journal of Finance*, 64(5):1985–2021, 2009.

Eric Beinstein and Andrew Scott. Credit Derivatives Handbook. *Corporate Quantitative Research*, 2006.

Frederico Belo, Vito D. Gala, and Jun Li. Government Spending, Political Cycles, and the Cross-Section of Stock Returns. *Journal of Financial Economics*, 107(2):305–324, 2013.

Laura Blattner, Luisa Farinha, and Francisca Rebelo. When Losses Turn Into Loans: The Cost of Undercapitalized Banks. *Working Paper*, 2019.

Patrick Bolton, Hui Chen, and Neng Wang. A unified theory of tobin's q, corporate investment, financing, and risk management. *The Journal of Finance*, 66(5):1545–1578, 2011.

Diana Bonfim, Geraldo Cerqueiro, Hans Degryse, and Steven Ongena. On-Site Inspecting Zombie Lending. *Working Paper*, 2020.

Jacob Boudoukh, Matthew Richardson, and Robert F. Whitelaw. Industry returns and the fisher effect. *The Journal of Finance*, 49(5):1595–1615, 1994.

Markus K. Brunnermeier and Lasse Heje Pedersen. Market Liquidity and Funding Liquidity. *The Review of Financial Studies*, 22(6):2201–2238, 2009.

Ricardo J. Caballero, Takeo Hoshi, and Anil K. Kashyap. Zombie Lending and Depressed Restructuring in Japan. *American Economic Review*, 2008.

Uday Chandra. Income Conservatism in the U.S. Technology Sector. *Accounting Horizons*, 25(2):285–314, 2011.

Mikhail Chernov, Lukas Schmid, and Andres Schneider. A Macrofinance View of U.S. Sovereign CDS Premiums. *Journal of Finance*, 75(5):2809–2844, 2020.

John H. Cochrane. Portfolio choice. 2007.

Lauren Cohen and Christopher J. Malloy. Mini West Virginias: Corporations as Government Dependents. *Working Paper*, 2016.

David J Denis and Valeriy Sibilkov. Financial constraints, investment, and the value of cash holdings. *The Review of Financial Studies*, 23(1):247–269, 2010.

Ruchith Dissanayake. Government Spending Shocks and Asset Prices. *Working Paper*, 2019.

Amy Dittmar and Jan Mahrt-Smith. Corporate governance and the value of cash holdings. *Journal of Financial Economics*, 83(3):599 – 634, 2007. ISSN 0304-405X.

Amy Dittmar, Jan Mahrt-Smith, and Henri Servaes. International corporate governance and corporate cash holdings. *Journal of Financial and Quantitative analysis*, 38(1):111–133, 2003.

Peter Easton and Jinhan Pae. Accounting conservatism and the relation between returns and accounting data. *Review of Accounting Studies*, 9(4):495–521, 2004.

Eugene F. Fama and Kenneth R. French. The Cross-Section of Expected Stock Returns. *Journal of Finance*, 47(2):427–465, 1992a.

Eugene F. Fama and Kenneth R French. The cross-section of expected stock returns. *Journal of Finance*, 1992b.

Eugene F. Fama and Kenneth R French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 1993.

Michael Faulkender and Rong Wang. Corporate Financial Policy and the Value of Cash. *Journal of Finance*, 2006.

Financial Accounting Standard Board. Statement of financial accounting standards no. 2. *Norwalk, Connecticut*, 1974.

C. Fritz Foley, Jay C. Hartzell, Sheridan Titman, and Garry Twite. Why do firms hold so much cash? a tax-based explanation. *Journal of Financial Economics*, 86(3):579 – 607, 2007.

Andrea Gamba and Alexander Triantis. The value of financial flexibility. *The Journal of Finance*, 63(5): 2263–2296, 2008.

Priyank Gandhi and Hanno Lustig. Size Anomalies in U.S. Bank Stock Returns. *Journal of Finance*, 70(2): 733–768, 2015.

Mark Grinblatt and Tobias J. Moskowitz. Predicting stock price movements from past returns: the role of consistency and tax-loss selling. *Journal of Financial Economics*, 71(3):541 – 579, 2004.

Seungjin Han and Jiaping Qiu. Corporate precautionary cash holdings. *Journal of corporate finance*, 13(1): 43–57, 2007.

Jarrad Harford, Sattar A. Mansi, and William F. Maxwell. Corporate governance and firm cash holdings in the us. *Journal of Financial Economics*, 87(3):535 – 555, 2008.

David Haushalter, Sandy Klasa, and William F. Maxwell. The influence of product market dynamics on a firm's cash holdings and hedging behavior. *Journal of Financial Economics*, 84(3):797 – 825, 2007.

Fumio Hayashi and Edward C. Prescott. The 1990s in Japan: A Lost Decade. *Review of Economic Dynamics*, 5(1):206–235, 2002.

Zhiguo He and Arvind Krishnamurthy. A Model of Capital and Crises. *The Review of Economic Studies*, 79 (2):735–777, 2012.

Zhiguo He and Arvind Krishnamurthy. Intermediary Asset Pricing. *American Economic Review*, 103(2): 732–770, 2013.

Zhiguo He, Bryan Kelly, and Asaf Manela. Intermediary Asset Pricing: New Evidence from Many Asset Classes. *Journal of Financial Economics*, 2017.

Takeo Hoshi and Anil K. Kashyap. Will the U.S. Bank Recapitalization Succeed? Eight Lessons from Japan. *Journal of Financial Economics*, 97(3):398–417, 2010.

Gur Huberman. External financing and liquidity. *The Journal of Finance*, 39(3):895–908, 1984.

Joost Impink, Martien Lubberink, Bart van Praag, and David Veenman. Did accelerated filing requirements and sox section 404 affect the timeliness of 10-k filings? *Review of Accounting Studies*, 17(2):227–253, 2012.

Narasimhan Jegadeesh. Evidence of predictable behavior of security returns. *The Journal of Finance*, 45(3): 881–898, 1990.

Narasimhan Jegadeesh and Sheridan Titman. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1):65–91, 1993.

Michael C. Jensen. Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review*, 76(2):323–329, 1986. ISSN 00028282.

Michael C. Jensen and William H. Meckling. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 1976.

Anil K. Kashyap, Owen A. Lamont, and Jeremy C. Stein. Credit Conditions and the Cyclical Behavior of Inventories. *Quarterly Journal of Economics*, 109(3):565–592, 1994.

Bryan Kelly, Lubos Pastor, and Pietro Veronesi. The Price of Political Uncertainty: Theory and Evidence from the Option Market. *Journal of Finance*, 71(5):2417–2480, 2016.

Chang-Soo Kim, David C. Mauer, and Ann E. Sherman. The determinants of corporate liquidity: Theory and evidence. *The Journal of Financial and Quantitative Analysis*, 33(3):335–359, 1998.

Thomas H. Klier and James Rubenstein. Detroit Back from the Brink? Auto Industry Crisis and Restructuring, 2008-11. *Economic Perspectives*, 36(2):35–54, 2012.

Dmitry Livdan, Horacio Sapriza, and Lu Zhang. Financially constrained stock returns. *The Journal of Finance*, 64(4):1827–1862, 2009.

Asaf Manela and Alan Moreira. News Implied Volatility and Disaster Concerns. *Journal of Financial Economics*, 123(1):137–162, 2017.

Wayne H. Mikkelson and M. Megan Partch. Do persistent large cash reserves hinder performance? *The Journal of Financial and Quantitative Analysis*, 38(2), 2003.

Merton H. Miller and Daniel Orr. A model of the demand for money by firms. *The Quarterly Journal of Economics*, 80(3):413–435, 1966.

Stewart C. Myers and Nicholas S Majluf. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 1984.

Hiroshi Nakaso. The financial crisis in Japan during the 1990s: how the Bank of Japan responded and the lessons learnt . *BIS Papers No. 6*, 2001.

Maureen O'Hara and Wayne Shaw. Deposit Insurance and Wealth Effects: The Value of Being "Too Big to Fail". *Journal of Finance*, 45(5):1587–1600, 1990.

Tim Opler, Lee Pinkowitz, René Stulz, and Rohan Williamson. The determinants and implications of corporate cash holdings. *Journal of Financial Economics*, 52(1):3 – 46, 1999.

Aydin Ozkan and Neslihan Ozkan. Corporate cash holdings: An empirical investigation of uk companies. *Journal of Banking & Finance*, 28(9):2103 – 2134, 2004.

Berardino Palazzo. Cash holdings, risk, and expected returns. *Journal of Financial Economics*, 104(1):162 – 185, 2012.

Lubos Pastor and Pietro Veronesi. Political uncertainty and risk premia. *Journal of Financial Economics*, 110(3):520–545, 2013.

Joe Peek and Eric S. Rosengren. Unnatural Selection: Perverse Incentives and the Misallocation of Credit in Japan. *American Economic Review*, 95(4):1144–1166, 2005.

Lee Pinkowitz and Rohan Williamson. What is the market value of a dollar of corporate cash? *Journal of Applied Corporate Finance*, 19(3):74–81, 2007.

Lee Pinkowitz, René Stulz, and Rohan Williamson. Does the contribution of corporate cash holdings and dividends to firm value depend on governance? a cross-country analysis. *The Journal of Finance*, 61(6): 2725–2751, 2006.

Raghuram G. Rajan and Luigi Zingales. Financial Dependence and Growth. *American Economic Review*, 88 (3):559–586, 1998.

Scott Richardson. Over-investment of free cash flow. *Review of accounting studies*, 11(2-3):159–189, 2006.

Landon J. Ross. Are Item 1A Risk Factors Priced? *Working Paper*, 2019.

Sharon Y. Ross. Zombie Asset Pricing. *Working Paper*, 2020.

Sharon Y. Ross. Government Risk Exposure: Zombies, Bailouts, and Government Suppliers. *Working Paper*, 2021.

Fabiano Schivardi, Enrico Sette, and Guido Tabellini. Credit Misallocation During the European Financial Crisis. *Working Paper*, 2019.

Steve Slater. Fears mounts about exodus of Northern Rock savings. *Reuters*, 2007.

Richard L. Smith and Joo-Hyun Kim. The combined effects of free cash flow and financial slack on bidder and target stock returns. *The Journal of Business*, 67(2):281–310, 1994.

Ross L. Watts. Conservatism in accounting part i: Explanations and implications. *Accounting Horizons*, 17 (3):207–221, 2003a.

Ross L. Watts. Conservatism in accounting part ii: Evidence and research opportunities. *Accounting Horizons*, 17(4):287–301, 2003b.