Credit Distortions in Japanese Momentum*

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Abstract

Persistent credit distortions have warped equity returns in Japan, where decades of subsidized bank credit to "zombie firms" suppressed momentum premiums. Controlling for zombies revives Japan's momentum effect: momentum earns significant alpha after adjusting for zombies, and momentum's expected return and Sharpe ratio triple. The zombie-adjusted factor commands a positive price of risk, becomes unspanned by other factors, and aligns more closely with international patterns. Why? Zombies depend on forbearance from their banks, and zombie losers' outsized betas to bank returns depress momentum. Analysis of syndicated loan data confirms that firms with forbearance-prone lenders drive Japan's persistently low momentum returns.

JEL Codes: G10, G12, G20, G28

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1 Introduction

Since the 1990s, Japanese banks have restructured loans to insolvent borrowers, commonly called zombie firms, to avoid recognizing losses on non-performing loans. In an environment of regulatory forbearance, those loans were repeatedly rolled over by banks, resulting in persistent credit distortions. The widespread presence of zombies depressed productivity and investment in Japan, as documented by Caballero et al. (2008). In this paper, I show that zombie firms distort asset pricing premiums and suppress momentum returns in Japanese equity markets. Accounting for the impact of zombies when constructing Japanese asset pricing factors brings Japan's momentum premium into closer alignment with international benchmarks. My findings show that momentum should be included in an asset pricing model for Japanese equities only after addressing the distortions caused by zombies.

Correcting for zombie distortions restores momentum as a robust risk factor in Japan. Historically, Japanese momentum has been weaker than in global markets and has failed to explain the cross-section of Japanese equities. This has led to longstanding questions about whether momentum is inherently spurious. My findings show that zombies attenuate the momentum premium in Japan: the momentum premium and Sharpe ratio triple after excluding zombie firms. Furthermore, removing zombies reduces the value premium toward global averages while preserving the negative correlation between value and momentum. Together, these adjustments align Japanese value and momentum patterns more closely with those observed in other developed markets. I also show momentum is unspanned by other factors and earns significant risk compensation only after accounting for zombie distortions.

The persistence of zombies in Japan is deeply tied to bank lending practices. Banks sustain zombies through loan forbearance. Zombies—and especially zombie firms with relatively lower past returns, which I define as zombie losers—are highly sensitive to bank returns. When bank returns are high, zombie losers have high returns, driving down the momentum premium in Japan. I use syndicated loan data to show that the distortions in value and momentum premiums stem from firms with bank lenders that are prone to forbearance.

I examine the effect of zombie firms on Japanese momentum and value through five key findings. First, zombie-adjusted value and momentum premiums align more closely with global averages. Excluding zombies from the sample triples both the mean return and Sharpe ratio of the momentum premium. This is a significant improvement and makes the momentum premium's Sharpe ratio statistically indistinguishable from global momentum. Momentum generates significant alpha only after excluding zombies. A higher momentum effect may be matched with a lower value effect given the well-documented negative relationship between value and momentum Asness et al. (2013). I find exactly that: the value premium falls when I exclude zombies and aligns more closely with global averages. Value and momentum maintain a strong negative relationship after excluding zombies.

Second, I use syndicated loan data to identify firms borrowing from banks inclined toward forbearance. Firms that borrow only from forbearance-inclined Japanese banks are more likely to have the opportunity to become zombies. I show that these firms exhibit high value and low momentum, driving the overall patterns observed in Japan. International banks should be less forbearance-inclined, and I show that their Japanese borrowers have value and momentum premiums closer to global averages. I show that firms with international lead arrangers have value and momentum premiums near international equity premiums.

Third, I show that momentum commands a positive price of risk only after accounting for zombies. I construct zombie-adjusted factors and use them in cross-sectional pricing tests. The zombie-adjusted momentum factor—constructed by either controlling for zombies or excluding them entirely—commands a positive price of risk. Fourth, I establish that other common factors fail to span the zombie-adjusted momentum factor, even though other factors span traditional, unadjusted momentum.

Finally, I argue that the weakness of momentum in Japan stems from the relationship between zombies and banks. Zombie firms are heavily dependent on banks, and their returns are highly sensitive to bank performance: zombies are more sensitive to bank returns than non-zombies. In particular, zombie losers exhibit a high covariance with bank returns. When banks perform well, zombie losers experience disproportionately strong returns, driving down momentum. In contrast, the returns of non-zombie winners and losers are less sensitive to bank returns, making non-zombie momentum less affected by fluctuations in bank performance. I show that months with the best 5 percent of bank returns account for a third of the difference between zombie momentum and non-zombie momentum.

Combined, these results show that persistent credit distortions reshape long-run asset pricing premiums. Short-term support to firms during crises, such as the COVID-19 pandemic, may well be necessary. But failure to restore a competitive environment over the long term can perpetuate zombie firms. These firms' returns distort common asset pricing premiums, such as momentum, due to their high covariance with bank returns.

Section 2 describes the data and factor construction. Section 3 shows the empirical results, with Section 3.1 showing zombie-adjusted value and momentum, Section 3.2 showing that forbearance-inclined lenders drive Japan's value and momentum results, Sections 3.3 and 3.4 discussing cross-sectional and spanning results, and Section 3.5 showing the role of zombies' high bank betas in driving low momentum. Section 4 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 exist outside of 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 (2022) 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 international value and momentum. International equities earn medium-term returns (Rouwenhorst, 2002), and Asness et al. (2013) find a robust negative correlation between value and momentum across many markets and asset classes. The low momentum effect in Japan has been noted by others (including Fama and French (2012) and Griffin et al. (2003)) and has led some to hesitate to include 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 Data

I use Japanese market data and accounting data from Datastream and Worldscope, covering the period from 1979 to 2024. The dataset includes the universe of Japanese stocks in Datastream and Worldscope. I restrict the sample to firms with a book value in the previous six months and at least 12 months of return history. I require firms to have Japanese yen prices available. Additionally, I exclude financial firms (including REITs), stocks with a share price less than $1 at the start of each month, and stocks without a share price at the start of the month. I also remove stock returns once they are dead, which I identify as three consecutive months of identical returns.

I follow the methodology of Asness et al. (2013) and focus on a sample of liquid stocks to facilitate comparisons with international value and momentum premiums. I rank stocks by market capitalization in descending order each month. Starting with the largest stock, I include stocks sequentially until the cumulative market capitalization reaches 90 percent of the total market capitalization for that month.

Throughout this paper, I use standard momentum and value signals to sort firms into groups and construct portfolios. The momentum signal is the cumulative return over the past 12 months, excluding the most recent month to avoid reversal effects (Jegadeesh (1990), Lehmann (1990)). The value signal is the book-to-market ratio, where book value is lagged by six months, to ensure data availability (Fama and French (1992), Fama and French (1993), Lakonishok et al. (1994)).

I sort firms into groups based on the value and momentum measures separately and create portfolios for each group. The top group of past returns consists of *winners*, while the bottom group consists of *losers*. Momentum returns are calculated by taking a long position in the winner portfolio and a short position in the loser portfolio. For value, *growth* firms belong to the lowest book-to-market group, and *value* firms belong to the highest book-to-market group. Value returns are defined as the difference between value and growth portfolios.

Momentum and value portfolio returns are estimated using three approaches: the premium, the strategy, and the factor. The premium is a straightforward high-minus-low portfolio, and the strategy and factor use the methodologies from Asness et al. (2013) and Fama and French (1992) (details below). A central contribution of this paper is filtering the sample to adjust for zombies, estimating momentum and value returns using these three methods, and comparing the resulting portfolios.

2.1 Identifying Zombies

I identify zombies using the methodology of Caballero et al. (2008), which involves comparing a firm's actual interest payment, $R_{i,t}$, to an estimated lower-bound $R^{\star}_{i,t}$. The lower-bound represents the interest payments a firm i could incur if it borrowed at no spread to the prime rate at time t:

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

where $S_{i,t}$ is short-term debt and $L_{i,t}$ is long-term debt, and r_t^s and r_t^ℓ 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:

$$X_{i,t} \equiv \frac{R_{i,t} - R_{i,t}^{\star}}{B_{i,t-1}} = r_{i,t} - r_{i,t}^{\star}. \tag{2}$$

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.

In their definition of zombies, Caballero et al. (2008) seek to identify firms that are receiving sufficient financial help from creditors despite the firms' low profitability. Following their approach, I define *crisp* zombies as companies with an interest-rate gap below 0 ($X_{i,t} < 0$). These firms borrow at below-market rates, indicating that they receive assistance from banks to sustain their operations. Since borrowing rates should reflect the firm's riskiness, only a select few firms should qualify to borrow at no spread to the prime rate. Firms with interest payments below $R_{i,t}^{\star}$ are, therefore, likely beneficiaries of credit distortions.

But such a measure is necessarily estimated with some noise. Caballero et al. (2008) identifies some companies as "fuzzy" zombie firms given the "fuzzy nature" in measuring sufficient financial support. Firms with an interest-rate gap just above zero also borrow at exceptionally low rates. In principle, only the highest-quality companies should borrow at effective rates near the prime rate, as most corporate borrowers typically face a nontrivial spread. Firms just above the negative gap cutoff likely benefit from regulatory forbearance by Japanese banks, and their returns—both the time series and cross-section—may be influenced by credit distortions. With this in mind, I define firms with interest-rate gaps between 0 and 50 bps ($X_{i,t} < 0.5$ percent) as *fuzzy* zombies. These firms face low borrowing costs that round to a 0 percent spread above prime borrowing rates.

Fuzzy and crisp zombies alike arise from credit distortions. Since this paper focuses on the impact of credit distortions on asset prices, I consider them jointly in a category of zombie firms in my empirical analysis. For robustness, I also show empirical results with only crisp zombies as a narrower definition.

This approach to identifying zombies may occasionally misclassify some high-quality firms as zombies. The most creditworthy firms can borrow at or near the prime rate due to strong banking relationships, and may even borrow below prime if banks are broadly offering low rates. However, given the widespread presence of zombies, it is unlikely that the identification method is principally capturing high-quality, bank-connected firms. One way to check the classification is by comparing the profitability of zombies and non-zombies. Table A.1 shows that zombies are, on average, less profitable than non-zombies. Zombies have lower returns on assets and equity, and they are more likely to exhibit negative profit margins. The paper's results are not mainly driven by low profitability, which I discuss further in Section 3.4. Moreover, Ross (2021) shows that zombie classification is not merely a proxy for bank dependence: zombies also benefit from government forbearance, which is reflected in their pricing.

Figure 1 shows the sample's proportion of crisp zombie firms. On average, 17 percent of firms qualify as crisp zombies. During the mid-1980s, the share of zombie firms was negligible, but it has steadily risen over time, reaching roughly 40 percent of firms. This aligns with the findings of Caballero et al. (2008). During the overlapping time frame, Caballero et al. (2008) documents a share of crisp zombies between 5 and 35 percent.[1]

Zombie status is highly persistent. Across firms, zombie status has an autocorrelation coefficient of over 95 percent. And switches from zombie to non-zombie, or vice versa, occur roughly 1.2 percent of the time. The interest-rate gap shows no significant correlation with firm size. Before removing small and illiquid stocks to restrict the sample to a liquid sample, the correlation between size and interest-rate gap is 0 percent, and size has a 1.4 percent correlation with the crisp zombie indicator and a 0.7 percent correlation with an indicator for crisp or fuzzy zombie. After refining the sample to the liquid set of stocks, the share of zombies increases from 22 percent to 64 percent, and size has a 2 to 3 percent correlation with indicators for zombie-ness.

Table 1 shows the average percent of zombies in each tercile of momentum and value separately. For momentum, I sort firms into three equal-sized groups based on their past returns. Winners are firms in the group with the highest past returns, and losers are firms in the group with the lowest past returns.

[1] This graph plots the share of crisp zombies in the raw dataset before restricting to the liquid sample to be directly comparable to Caballero et al. (2008)'s figure, which uses estimates assuming a cutoff of 0 percent. However, Caballero et al. (2008) also consider fuzzy zombies.

I calculate the share of firms that are zombies in each tercile. In the full data, crisp and fuzzy zombies combined make up 50 percent to 60 percent of firms in each momentum tercile. There are slightly more zombies in the loser tercile. 57 percent of firms in the bottom tercile happen to be zombies; 54 percent of firms in the top tercile are zombies. For value, I sort firms into three groups based on book-to-market. 59 percent of firms in the top tercile are zombies, compared to 51 percent of firms in the bottom tercile.

Next, I remove crisp zombies from the sample and resort the remaining firms, consisting of non-zombies and fuzzy zombies, into buckets based on new momentum and value breakpoints. Table 1 shows that there are now no crisp zombies in any of the momentum terciles. Using the new breakpoints, 26 percent of loser firms happen to be fuzzy zombies compared to 24 percent of firms in the top tercile. I remove all firms considered zombies in the bottom panel and confirm that all the buckets have no zombies remaining.

A potential concern is that the higher concentration of zombies among high value stocks and past loser stocks could lead to lower momentum after their removal. I address this in three ways. First, after excluding zombies, I reform the tercile buckets using new cutoffs and re-sort the firms. By filtering zombies first and then forming the tercile buckets second, I ensure that the zombie's characteristics do not bias the breakpoints that I use to form portfolios. This approach of excluding firms where there is a prior that they exhibit different behaviors is standard in literature: for example, Fama and French (1992) drop financials stocks, and Asness et al. (2013) exclude stocks with prices less than $1 and firms in the bottom 10 percent of market capitalization. My approach to dropping zombies is follows these approaches: drop the idiosyncratic firms and then calculate breakpoints.

Second, Table 1 shows that the difference in the share of zombies between momentum terciles is only 3 percent (57 percent for the losers versus 54 percent for the winners). This difference in zombie share narrows to 2 percent after removing crisp zombies and re-sorting using new breakpoints (26 percent versus 24 percent). Excluding both crisp and fuzzy zombies from the sample before calculating breakpoints means that both the high and low terciles mechanically have identical—zero—zombie shares.

And third, this concern suggests that changes in past losers and high value stocks drive the results. However, Table 2 indicates that the improvement in momentum arises from increased returns in past winner returns. The top tercile returns increase by 2.8 percent, compared to an increase of 0.3 percent for past losers. Similarly, the reduction in the value premium is driven by higher returns for growth stocks rather than lower returns for value stocks.

2.2 Measuring Value and Momentum

I estimate momentum and value portfolio returns using three approaches: the premium, the strategy, and the factor. All three are long-short portfolios designed to capture the effects of momentum and value. These approaches facilitate both time-series and cross-sectional comparisons, allowing insights into how zombie firms influence returns in Japan.

The premium and strategy returns are analyzed in the time series in the literature. I compare the returns using the full sample and a filtered sample that removes zombies. I also compare the premium and strategy returns to off-the-shelf international counterparts of value and momentum. The empirical results show that the effect of zombies is robust to using either the premium or strategy.

The factors are commonly used in the cross-section and are constructed analogously to the methodology of Fama and French (1993). Unlike the premium or strategy, the factor measures a risk factor (value or momentum) while controlling for other risks by double or triple sorting. I construct zombie-adjusted factors using two approaches to compare to standard factors used in cross-sectional tests: one approach that filters zombies entirely and another approach that triple sorts value by both size and zombie-ness. The empirical results are robust to using either approach to calculate zombie-adjusted factors.

Value and Momentum Premium The momentum and value premium are simple "high-minus-low" portfolio returns. I sort firms into three equal-sized groups based on the momentum and value signals, calculate value-weighted portfolio returns of each group, and calculate the premium as the difference between the returns of the top and bottom portfolios.

As discussed above, the momentum signal is the cumulative return over the past 12 months, excluding the most recent month. Firms are sorted into three groups (winners, neutrals, losers) based on past returns. The momentum premium is calculated as the return difference between value-weighted winner and loser portfolios.

The value signal is the book-to-market ratio. Firms are grouped into value (high book-to-market), neutral, and growth (low book-to-market) categories. The value premium is the return difference between the value and growth portfolios.

Value and Momentum Strategy To account for outliers, I also construct momentum and value strategies using the ranking-based methodology of Asness et al. (2013).[2] These zero-cost

[2] Asness et al. (2013) call the strategy "factors" in their paper. I call it a strategy to avoid confusion with the Fama–French "factors".

portfolios weight securities based on their rank within the signal distribution, reducing the influence of extreme observations. The strategies provide a robustness check, with results aligning closely with those derived from the premium approach.

I construct the momentum strategy and value strategy in the same way as Asness et al. (2013).The strategy factor return for each signal $S \in (\text{value}, \text{momentum})$ is

$$r_t^S = \sum_i w_{it}^S r_{it} \tag{3}$$

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

$$w_{it}^S = c_t \underbrace{\left(rank(S_{it}) - \frac{1}{N} \sum_i rank(S_{it}) \right)}_{x_{it}} \tag{4}$$

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

Value and Momentum Factors For cross-sectional analysis, I use the standard Fama–French factors *HML* and *WML*. Fama and French (1993) constructs *HML* by using a double sort on size and value. The double sort is designed to isolate the risk of a characteristic; for example, if size and book-to-market are highly correlated, then a long-short value factor is also a long-short size factor. Double sorting helps reduce this effect by carefully constructing portfolios that do not systematically covary with the other characteristic. I sort firms into two size groups (Big and Small) and three value groups (High, Mid, Low) separately and make portfolios (S/L, S/M, S/H, B/L, B/M, B/H) from the intersection of the two size groups and three value groups.

HML is defined as the difference between the average of the returns on the two high book-to-market portfolios and the average of the returns of the two low book-to-market portfolios:

$$HML = \frac{\text{High/Small} + \text{High/Big}}{2} - \frac{\text{Low/Small} + \text{Low/Big}}{2}. \tag{5}$$

WML is constructed by sorting firms into two size groups and three momentum groups (Winners, Neutral, Losers) and forming six portfolios from the intersection (S/L, S/N, S/W, B/L, B/N, and B/W). *WML* is the difference between the average of the two winner portfolio returns and the average of the two loser portfolio returns:

$$WML = \frac{\text{Winner/Small} + \text{Winner/Big}}{2} - \frac{\text{Loser/Small} + \text{Loser/Big}}{2}. \tag{6}$$

The factor construction gives value and momentum factor-mimicking portfolios. For example, for *HML*, Fama and French (1993) write:

> The portfolio *HML* mimics the risk factor in returns related to book-to-market equity . . . Thus the difference between the two returns should be largely free of the size factor in returns, focusing instead on the different return behaviors of high- and low-BE/ME firms.

Zombie-Adjusted Value and Momentum Factors To study the impact of zombies on the factors, I construct zombie-adjusted momentum WML_{ZA} and value HML_{ZA} using two approaches. The first approach removes zombies before constructing factors using standard double-sorting methods. The second approach triple-sorts to control for the effect of zombies. Both approaches yield similar asset pricing results. Either of the two approaches works if I consider all zombies together or crisp zombies alone.

The first approach involves removing zombies from the sample and constructing the factors using the conventional definitions of factor-mimicking portfolios. This method estimates the returns of the value and momentum factors in a hypothetical scenario where zombies do not exist. First, I exclude zombies from the sample. Second, I proceed with the approach described above to calculate analogous versions of value and momentum described in equations 9 and 10.

I split the data into equal-sized groups by value (High, Middle, Low) and size (Small, Big) to calculate the zombie-adjusted value factor. I then form six double-sorted portfolios: High/Big, High/Small, Middle/Big, Middle/Small, Low/Big, and Low/Small. The returns of these portfolios are used to compute the zombie-adjusted value factor using the following equation:

$$HML_{ZA} = \frac{\text{High/Small} + \text{High/Big}}{2} - \frac{\text{Low/Small} + \text{Low/Big}}{2}. \tag{7}$$

I construct WML_{ZA} using the same approach. After excluding zombies, the data are divided into equal-sized groups by past returns (Winner, Middle, Loser) and size (Small, Big). I form six double-sorted portfolios: Winner/Big, Winner/Small, Middle/Big, Middle/Small, Loser/Big, and Loser/Small. The returns of these portfolios are used to compute the zombie-adjusted momentum factor using the following equation:

$$WML_{ZA} = \frac{\text{Winner/Small} + \text{Winner/Big}}{2} - \frac{\text{Loser/Small} + \text{Loser/Big}}{2}. \tag{8}$$

The second approach keeps zombies in the dataset and controls for their influence in the factor construction process by using a triple-sort approach. The triple sort controls for the influence of zombies in factor constructions by balancing their exposure across the portfolios. This method parallels the method in Fama and French (1993), where SMB and HML are designed to capture size and value effects, respectively, while also minimizing the confounding effect of other characteristics like book-to-market or size.[3] Triple sorts are also common in the literature; for example, Hou et al. (2015) use a triple-sort method when constructing factors to control for covarying variables.

I use the triple-sort approach to ensure that the influence of zombies is evenly distributed across the long and short portfolios. The resulting factor-mimicking portfolios should be largely free of the influence of zombies (as well as size) and instead capture the true value and momentum returns.

Specifically, I independently sort the data into equal-sized groups based on value (H, M, L), momentum (W, M, L), size (S, B), and zombie-ness (zombie (Z), not zombie (N)). I then form triple-sorted portfolios using the value, size, and zombie-ness sorts; separately, I form triple-sorted portfolios using the momentum, size, and zombie-ness sorts.

These triple-sorted portfolios are then used to compute the zombie-adjusted factors, ensuring that the effects of zombie-ness are roughly balanced across the long and short portfolios so as to capture the returns attributable to value and momentum. The zombie-adjusted value and momentum factors are calculated as follows:

$$HML_{ZA} = \frac{\text{H/S/Z} + \text{H/S/N} + \text{H/B/Z} + \text{H/B/N}}{4} - \frac{\text{L/S/Z} + \text{L/S/N} + \text{L/B/Z} + \text{L/B/N}}{4} \tag{9}$$

[3] Fama and French (1993) create six portfolios (S/L, S/M, S/H, B/L, B/M, B/H) and define SMB as $\frac{1}{3}(\text{S/L}+\text{S/M}+\text{S/H}) - \frac{1}{3}(\text{B/L}+\text{B/M}+\text{B/H})$ and define HML as $\frac{1}{2}(\text{S/H}+\text{B/H}) - \frac{1}{2}(\text{S/L}+\text{B/L})$. Fama and French (1993) write, "SMB is the difference between the returns on small- and big-stock portfolios with about the same weighted-average book-to-market equity. This difference should be largely free of the influence of BE/ME, focusing instead on the different return behaviors of small and big stocks." Similarly, since HML is constructed by double sorting book-to-market with size "[t]he two components of HML are returns on high- and low-BE/ME portfolios with about the same weighted-average size. Thus [HML] should be largely free of the size factor in returns, focusing instead on the different return behaviors of high- and low- BE/ME firms."

and

$$WML_{ZA} = \frac{\text{W/S/Z} + \text{W/S/N} + \text{W/B/Z} + \text{W/B/N}}{4} - \frac{\text{L/S/Z} + \text{L/S/N} + \text{L/B/Z} + \text{L/B/N}}{4}. \tag{10}$$

This second approach isolates the value and momentum premiums by accounting for distortions caused by zombies and size effects. This is because the factors are long and short (with equal weight) the same number of portfolios loading on zombie-ness and size, leading to a zero net weight on size and zombie-ness. Each zombie-adjusted factor is long two zombie portfolios and short two zombie portfolios with the same weight on each portfolio. Thus, the net weight of zombie-ness in the zombie-adjusted factors is zero. The factors largely strip out the effect of zombie-ness and size.[4]

2.3 Syndicated Loans Data

I also use data from Loan Pricing Corporation (LPC) Dealscan, which has data on Japanese firms' syndicated loans starting in 1988, to establish lending relationships between banks and borrowers. I match Datastream tickers to Compustat data using ISIN identifiers and link the Compustat data to Dealscan data using the Roberts Dealscan-Compustat Linking Database. This method matches 25 percent of Japanese loan tranches to specific Datastream tickers, and 52 percent of my liquid Datastream data includes firms with at least one syndicated loan.

Using the Dealscan data, I classify the lead arranger for each loan and categorize firms based on their lending relationships. Firms are grouped into those with Japanese lead arrangers and those with international lead arrangers. Since many firms have multiple syndicated loans, I consider the Japanese borrower-lender relationship to start from the earliest syndicated loan date.

3 Empirical Results

I now show that the continued existence of zombie firms in Japan suppresses momentum returns. To explore how Japanese momentum might behave in the absence of these distortions, I estimate momentum returns after excluding zombie firms. This approach reveals that

[4] WML_{ZA} and HML_{ZA} have zero net weight on zombie portfolios because they have a 0.5 weight in the long leg on zombie portfolios and a 0.5 weight in the short leg on zombie portfolios. WML_{ZA} has a weight of $\frac{1}{4} + \frac{1}{4} = \frac{1}{2}$ on zombie portfolios on the long leg coming from portfolios W/S/Z and W/B/Z and a weight of $\frac{1}{4} + \frac{1}{4} = \frac{1}{2}$ on zombie portfolios in the short leg coming from portfolios L/S/Z and L/B/Z.

removing zombies significantly improves both the return and Sharpe ratios of Japanese momentum, aligning it more closely with international benchmarks. Zombies distort not only the time-series momentum premium but also the cross-section of returns. After accounting for zombies, momentum earns a significant price of risk and becomes unspanned by other asset pricing factors.

Zombie firms persist due to banks' forbearance on loans, and this relationship lies at the core of their influence on momentum in Japan. Using syndicated loan data, I show that firms with lenders prone to forbearance are the primary drivers of Japan's suppressed momentum. Moreover, zombie firms—and particularly zombie losers—have high bank beta. Periods of strong bank performance correspond to declines in zombie momentum and, consequently, overall momentum returns.

3.1 Zombie-Adjusted Value and Momentum

Table 3 presents the annualized returns for the value and momentum premiums, as well as the signal-weighted strategies, calculated both for the full dataset of liquid stocks and for a subset excluding zombies. When using the full dataset, Japan's unadjusted momentum premium is 0.91 percent and statistically indistinguishable from zero, consistent with the well-documented weakness of momentum in Japan.

Removing zombies dramatically improves momentum returns. After dropping zombies, the momentum premium increases from 0.91 percent to 2.99 percent, and the Sharpe ratio more than triples from 0.05 to 0.15. Similarly, the momentum strategy's return and Sharpe ratio more than double. The table also reports the alpha and t-statistic from a time-series regression of the momentum premium and strategy on the Fama French 3-factor model. In the full dataset, alpha is small and insignificant; however, after removing zombies, the momentum premium and strategy can generate significant alpha at the 10 percent level.

Conceptually, removing zombies allows me to explore a counterfactual scenario where widespread credit distortions caused by zombie lending do not exist. Of course, there are both advantages and disadvantages to this approach. The advantages are that it is both simple and that dropping firms from the sample before conducting sorts are standard in the literature. But the disadvantage is that it is impossible to measure momentum in a counterfactual world since, as Caballero et al. (2008) show, zombies distort competitive processes and make some industries sclerotic. With this caveat, I show that in this counterfactual world, with zombies removed, the momentum premium in Japan improves significantly and is a priced risk factor in the cross-section.

One concern is that zombie identification is random or inconsistent, leading to noise. This is not the case: firms identified as zombies typically remain zombies. Firms rarely switch between zombie and non-zombie status. For robustness, I randomly drop half the data in the last two columns in Table 3 and calculate value and momentum returns. Randomly dropping half the data does not meaningfully improve momentum returns. By dropping half the sample, the mean and Sharpe ratios show minimal improvement, and these subsamples fail to earn significant alpha. This highlights that removing zombies is not equivalent to randomly excluding half the sample; instead, dropping zombies reflects removing firms that are consistently identified and have a systematic impact on asset pricing distortions.

The value premium in the full dataset is 11.36 percent and statistically significant. Strong value returns are not surprising given the strong negative correlation between value and momentum observed across many markets (Asness et al., 2013).[5] Excluding zombies reduces the value premium and strategy returns to roughly 8 percent. Value continues to deliver strong, significant returns. It maintains a significant alpha, which I calculate relative to a 3-factor model that uses the market return, size, and momentum factors. Importantly, adjusting for zombies does not eliminate the value effect in Japan.

Removing zombies also preserves the strong negative correlation between value and momentum documented by Asness et al. (2013) across many asset classes. They find that countries with higher value tend to have lower momentum, and vice versa. They argue, then, that investing strategies that combine both value and momentum are optimal since the negative correlation between the two provides a natural hedge for periods when one underperforms. Asness (2011) argues that the high value premium in Japan, combined with the negative correlation between value and momentum, implies that momentum should be low in Japan.

Table 4 shows that the zombie adjustment preserves this negative correlation between value and momentum: the correlation coefficient between value and momentum is -0.59 without zombies, compared to -0.57 with zombies. For the strategies, the correlation is -0.60 without zombies, compared to -0.62 with zombies. The exclusion of zombies does not alter the fundamental relationship between value and momentum. Instead, the persistent negative covariance between these factors highlights their complementarity, supporting the argument that value and momentum should be considered jointly rather than in isolation. Motivated by this time-series covariance, in Section 3, I explore the joint effects of value and momentum through cross-sectional regressions.

[5] Table 4 shows that this strong correlation between value and momentum persists even after adjusting for zombies.

One potential concern is the lack of statistical significance in the momentum premium and strategy returns reported in Table 3. I address this in four ways. First, I note that removing zombies leads to significant alpha for the momentum premium and strategy at the 10 percent level. Second, examining factor returns in isolation can overlook the broader role of covariance. To provide a fuller picture, I evaluate zombie-adjusted momentum in conjunction with other factors in cross-sectional regressions and spanning tests in Sections 3.3 and 3.4 to explore the covariance between factors.

Third, Table 5 shows that the average returns and Sharpe ratio improvements after excluding zombies are statistically significant. The table reports p-values from comparing unadjusted and zombie-adjusted momentum. I use a t-test to compare mean returns and apply the statistical method from Ledoit and Wolf (2008) to compare Sharpe ratios. A small p-value means that we would fail to reject the null hypothesis that the two premiums are equal. In other words, a small p-value indicates the two tested returns have statistically different returns or Sharpe ratios.

The table shows that momentum estimated using full data is statistically smaller than momentum with zombies removed. In the first column and row, I test whether the momentum premium in the full data equals the momentum premium in the dataset with crisp and fuzzy zombies removed. The null hypothesis is that they are equal, and the alternative hypothesis is that the momentum premium in the full dataset is larger than momentum with zombies removed. The small p-value indicates that we would reject the null in favor of the null hypothesis, which indicates the momentum premium is significantly larger after zombies are removed.

In the second column, I use the method from Ledoit and Wolf (2008) to test whether the Sharpe ratios are equal. Ledoit and Wolf (2008) construct a time-series bootstrap confidence interval for the difference of the Sharpe ratios. I use a block size of 5 and 5000 simulations and report the p-value of the test that the two Sharpe ratios are not equal in Table 5. The small p-values from the Sharpe ratio comparison test indicate that the Sharpe ratios of the two momentum premiums also differ statistically at the 10 percent level. Momentum is larger after removing zombies. In contrast, the momentum premium using the full data is indistinguishable from the momentum premium using a random half of the data. A similar trend follows for the momentum strategy, value premium, and value strategy: removing zombies leads to statistically larger average returns and Sharpe ratios, but removing random firms does not.

Fourth, it is important to note that the zombie adjustment is limited by the precision of using the interest-rate gap calculated from publicly available data to identify zombies. The interest rate gap is necessarily coarse and limited to the granularity of quarterly financial filings. Ideally, I would identify zombies using loan data for each firm with characteristics such as interest rate, maturity, and information on covenants. Moreover, since research using the interest-rate gap to identify zombies is public knowledge, it is likely firms and banks work to avoid the appearance of zombie lending—window-dressing that is not possible to identify using public information. These facts introduce noise into precisely measuring the zombie-adjusted momentum premium. This bias would manifest as the misclassifying of true zombies as non-zombies, which likely pushes the zombie-adjusted momentum premium down. Why? Table 2 shows that excluding the zombies that I can identify using public data increases the momentum premium. Therefore, my zombie-adjusted momentum estimate represents a lower bound subject to the likely bias in the public data.

Removing zombies not only improves momentum returns but also helps align Japan's anomalies closer to global averages. Table 6 compares value and momentum in Japan to the premiums and strategies in other countries. The Global Average is the equal-weighted mean of 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. (2013).

In the full data, Japanese momentum is just 11 percent of the global average, but it jumps to 50 percent after adjusting for zombies. The Sharpe ratio also improves notably (from 9 percent of the global average to 38 percent). Looking at the momentum strategy, relative to the global average or global factor, shows similar results: Japanese momentum is much closer to momentum in other developed market countries after adjusting for zombies.

Value also moves closer to global figures, declining from three to six times the global average. Figure 2 shows this graphically. Value in Japan is exceptionally large, and 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.

The Japanese momentum premium with zombies removed is statistically indistinguishable from global ex-Japan momentum. Table 7 shows the *p*-values from statistical tests comparing means and comparing Sharpe ratios. A large *p*-value means we fail to reject the null hypothesis that the two returns or Sharpe ratios are equal. Thus, Japanese momentum is statistically similar to global momentum after adjusting for zombies. The momentum premium using the full data differs from global momentum in the means and Sharpe ratios. After adjusting for zombies, Japanese value has a similar Sharpe ratio to global value.

3.2 Syndicated Loan Lending Relationships

Zombies arise from regulatory forbearance in Japan. By allowing zombie firms to continue to exist, Japanese banks can avoid capital writedowns, and zombies' subsidized credit should come from Japanese lenders. By contrast, 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 provides a distinct measure of zombie-ness that does not rely on publicly available interest-rate gap data. 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 use Dealscan syndicated loan data to identify firm-lead arranger lending relationships (see Section 2 for details). Then, I sort firms into two groups based on their lead arranger and calculate value and momentum for the two groups. The first group has only Japanese lead arrangers, and the second group has international lead arrangers.

Table 8 shows the value and momentum premium for these two groups and the full sample, calculated over the same time period. Firms with only Japanese lead arrangers have negative momentum, and value is also quite high for these firms. This result shows that firms with forbearance-inclined Japanese lenders drive the overall low momentum in Japanese equities. This adds to the evidence that forbearance by banks in Japan leads to zombies, whose returns drag down momentum.

By contrast, Japanese firms with international lenders earn positive momentum returns. These firms with international lead arrangers have a momentum Sharpe ratio of more than double the full-sample premium. These firms with international lenders may have less access or reliance on continued subsidized credit. Firms in this group are less likely to be zombies, and their momentum returns are closer to momentum premiums in other countries without zombies.

As a robustness test, I also 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.[6] The identifying assumption is that banks requiring capital injections were the most likely to practice forbearance on their loans and, consequently, the most likely to lend to zombie firms. If zombies drive low momentum and banks needing capital injections are most likely to forbear on their loans, then firms borrowing from these banks should also have low momentum because they are likely zombies.

Table 8 shows the momentum premium for firms grouped on whether their lenders had capital injections. Firms borrowing from capital injection banks have lower momentum than the full sample; firms borrowing from other banks have higher momentum than the full sample. The result supports the prior that the latter group, who presumably have less forbearance, have higher momentum. The results are consistent with the lead arranger results even though many of the 21 banks have had mergers and subsequently ceased to exist as lenders in the sample. After a merger, the lending influence would be somewhat limited since the pre-merger bank would no longer be identified as a lender to new firms.

3.3 Zombie-Adjusted Cross-Sectional Pricing

Importantly, zombies revive Japanese momentum not only in the simple time-series return but also in the cross-section and in relation to other factors like value. I show that Japanese value and momentum factors can price the cross-section of Japanese equities only after the factors are adjusted for zombies.

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:

$$R^e_{i,t} = \alpha_i + \beta'_{i,f}\mathbf{f}_t + \varepsilon_{i,t},\ i = 1, \ldots, N,\ t = 1, \ldots, T, \tag{11}$$

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 11:

$$\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f + \xi_i,\ i = 1, \ldots, N, \tag{12}$$

where λ_f gives the factors' prices of risk. Intuitively, if a portfolio covaries positively with a

[6] 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. Note that many of the banks that received a capital injection later merged. I do not consider these newly merged banks as capital injection lenders.

factor ($\beta_{i,f} > 0$), and that factor represents a source of risk, the price of risk (λ_f) should be positive, reflecting the required compensation for bearing exposure to that risk.

Table 9 shows the price of risk from cross-sectional regressions of 25 size-and-book-to-market portfolios in Japan. The regressions began in November 1990, the first observation for *WML* in Japan. The results show that momentum has a significant price of risk only after the factors are adjusted for zombies.

The first three columns use unadjusted factors. Column 1 is CAPM; column 2 is the Fama and French (1993) 3-factor model; column 3 is the Carhart (1997) 4-factor model, which includes momentum, *WML*. In column 3, the results with the unadjusted factors show that momentum has a marginally significant price of risk.

The remaining columns use zombie-adjusted factors HML_{ZA} and WML_{ZA}. 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 zombie adjustment also allows for more efficient risk exposure. To see this, I consider the annualized increase in expected risk premium associated with a one standard deviation increase in a portfolio's beta to momentum. The increase is 0.54 percent for unadjusted momentum *WML*, compared to an estimated 2.2 to 2.8 percent for the zombie-adjusted momentum factors.

Adjusting for zombies aligns the portfolios' average excess returns with the portfolios' betas to value and momentum factors. Figure 3 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 4 plots the portfolios' betas to the momentum 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.[7]

[7]The slope is significant regardless of whether I drop zombies or triple-sort zombies in the construction of

Some potential concerns with the cross-sectional results are that a zombie-ness factor should be included in the model separately, rather than adjusting the other factors for zombie-ness, or that the zombie-adjusted factors should be constructed differently. I discuss this further in the Appendix and show that these zombie-adjusted factors—constructed by either removing zombies or triple-sorting to control for zombies—robustly earn compensation for risk and are consistently unspanned by other factors.

3.4 Spanning Tests

Spanning tests show whether a factor's economic content is contained in a linear combination of other factors. I show that Japanese momentum is unspanned by other factors only after adjusting for zombies. In other words, the evidence indicates that momentum should be included in the model only after the factor is adjusted for zombies.

Table 10 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. Each row shows the results of regressing the variable on the left-most column on factors in the other columns. The insignificant intercept on the WML row means that the standard Japanese momentum factor is spanned by the other factors. This would suggest that momentum does not need to be included in the model.

The zombie adjustment paints a different picture of the role of momentum. Panel B uses zombie-adjusted factors HML_{ZA} and WML_{ZA}, constructed by dropping crisp zombies. Zombie-adjusted momentum has a significant intercept and is unspanned by existing factors. The spanning tests support the inclusion of zombie-adjusted momentum in cross-sectional regressions.

Panels C, D, and E use other zombie-adjusted factors in the spanning tests. Panel C drops crisp and fuzzy zombies. Panel D uses the triple-sort method discussed in Section 2.2 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 covariance between value and momentum: the zombie adjustment does not affect the negative correlation between value and momentum.

An important concern is that zombie-ness is a restatement of a firm quality factor. Caballero et al. (2008) classify zombie firms based on their interest-rate gap rather than by operating characteristics like productivity or profitability metrics. But they show that zombies tend

WML_{ZA}.

to be low-productivity firms. Quality factors are closely related to profitability, and there may be concern that adding a quality factor may change the results. In the online appendix section A, I show that zombie-adjusted factors are not spanned by common quality factors in Japan. Controlling for zombies is not just a reincarnation of controlling for the quality or profitability anomaly.

Table A.2 adds the three Japanese quality factors—*RMW* (Robust Minus Weak), *QMJ* (Quality Minus Junk) and *BAB* (Betting Against Beta)—individually to the spanning tests. Each value in the table represents the intercept or t-statistic 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*. Panel A shows that the unadjusted Japanese momentum factor WML is spanned by the other Japanese factors, including the quality factors.

In panel B, the spanning tests swap out the value and momentum factors to the zombie-adjusted versions constructed by removing crisp zombies. Zombie-adjusted momentum has a significant intercept regardless of which quality factor is used in the regression, meaning zombie-adjusted momentum is not spanned by the other factors, even if we include quality. Panels C, D, and E use different forms of the zombie-adjusted value and momentum factors. Across all the specifications, zombie-adjusted momentum WML_{ZA} is not spanned by quality.

3.5 Zombies Covariance with Bank Betas Drives Momentum

Zombies would cease to exist without banks forbearing on their loans. Therefore, the relationship between banks and zombies is critical for zombie returns and, thus, momentum. I show that zombies' returns significantly covary with bank returns, and that months with strong bank returns correspond to weak zombie momentum and thus lower momentum overall.

Zombies have a higher beta to bank returns than non-zombies, and zombie losers have a particularly high bank beta. When banks have high returns, zombie losers have high returns, driving down momentum. Non-zombie momentum is not affected by bank returns in the same way since non-zombie winners and losers have similar bank betas. I find that the difference between zombie and non-zombie momentum widens significantly when banks have strong returns. Months with the top 5 percent of bank returns account for 33 percent of the difference between zombie momentum and non-zombie momentum.

Zombies have significantly higher bank beta than non-zombies, even after controlling for the market return. Strong bank returns support zombie returns and has a differential effect between zombie and non-zombie returns. I construct *Zombie* and *Non-zombie* factors as the value-weighted excess returns of zombie and non-zombie firms separately. In Table A.3, I calculate a simple bank beta by regressing the *Zombie* factor on Japanese bank returns.[8] I include fixed effects, but the results are similar excluding these controls. If bank returns increase by 1 percent in a month, *Zombie* returns increase by 0.6 percent on average, and *Zombie* significantly outperform *Non-zombie* by 0.07 percent. This outperformance holds even if we control for the market return.

There is also a differential effect *within* zombies: zombie losers have higher bank beta than zombie winners, and this leads to low overall momentum when we include zombies. This result holds when controlling for market returns. I form four value-weighted portfolios of zombie winners, zombie losers, non-zombie winners, and non-zombie losers. Table A.4 shows the bank beta of these four portfolios. All four portfolios have significant bank beta, but zombie losers have the highest bank beta. Panel C shows that zombies have a larger beta to bank returns when controlling for market returns.

One concern is that bank returns are driven by zombie returns rather than the other way around. The bank beta regression results reflect significant correlations, highlighting comovement rather than a causal relationship. Determining causality is challenging; however, if zombie returns were the primary driver of bank returns or caused substantial volatility, banks would likely reconsider their involvement in zombie lending. For the purposes of my paper, the critical point is that zombie returns exhibit strong covariance with bank returns, a pattern not observed with non-zombie returns. Japanese momentum is low due to zombies and an important component of the zombie drag on Japanese momentum is the covariance between zombie returns and bank returns.

To better understand how the relationship between bank returns and zombie returns might contribute to Japanese momentum, I study the divergence between zombie momentum and non-zombie momentum by looking at the difference between the two. This difference equals (Zombie Winners − Zombie Losers) − (Non-zombie Winners −Non-zombie Losers). Zombie and non-zombie winners and losers are constructed using the same breakpoints (the cutoffs used for the full data). In this way, the overall momentum series combines value-weighted zombie and non-zombie momentum.

Figure 5 shows the cumulative difference between zombie and non-zombie momentum returns. Over time, there is a widening between zombie and non-zombie momentum. Since Table A.3 and A.4 show that zombies, non-zombies, and each leg covaries with bank returns, I test

[8] The bank return is the value-weighted excess return of firms in the “banks” industry group.

whether top bank return months contribute to the widening between zombie and non-zombie momentum. This analysis is also motivated by the results in Daniel and Moskowitz (2016), which shows that momentum has substantial time-series variation and that there are large differences in the market betas of winner and loser portfolios. I add to Figure 5 the cumulative difference between zombie and non-zombie momentum in months with the top 5 percent of bank returns, and Figure 6 plots the contribution of the 5 percent of months to the overall difference. The results show that the divergence between zombie and non-zombie momentum is driven by periods of strong bank returns; a handful of months with strong bank returns account for a third of the cumulative difference.

In the online appendix, I formally test whether there is a significant divergence between zombie and non-zombie momentum in the months with high bank returns. Table A.5 regresses each of the four legs, zombie momentum, non-zombie momentum, and the difference in momentum on indicator variables for months with the top 5 percent of bank returns and months with the top 5 percent of market returns. The results show that the difference between zombie and non-zombie momentum widens significantly in top bank return months due to declines in zombie momentum, which are driven by strong zombie loser returns in these months. Panel A shows that all four legs have higher returns in top bank return months. Only zombie momentum returns are substantially lower in these months. Non-zombie momentum is statistically the same as in other months. The result is a significant widening in the difference between zombie and non-zombie momentum. In Panel B, I show that months with top market returns don't have the same effect on the difference in momentum. In these months, zombie and non-zombie momentum are both lower, but the decline is similar in magnitude across the two momentum returns.

Panel C regresses returns on indicators for both top bank return months and top market return months. Column 1 shows that the difference between zombie and non-zombie momentum widens significantly in top bank return months, even after controlling for top market return months. This is due to significant drops in zombie momentum in these months (column 2). In contrast, Column 3 shows that non-zombie momentum isn't substantially lower in months with high bank returns after controlling for months with top market returns. Ultimately, the combined results show that zombie losers' strong returns in top bank return months lead to low momentum for zombie and Japanese equities overall.[9]

[9] A potential concern is that zombie losers' outperformance is driven by return reversal. If return reversal were the primary driver of zombie loser returns, there would be a negative coefficient on lagged returns. In this way, lower past returns lead to higher subsequent returns. Table A.6 regresses the returns of the zombie factor and the zombie loser portfolio on lags of itself. The coefficients are primarily insignificant, indicating that past returns of zombie losers are not associated with future returns. The regression evidence shows

While the primary focus of these results is on the drag that zombie momentum exerts on overall Japanese momentum, the regression also suggests that zombie momentum is stronger than non-zombie momentum outside of top bank return months. However, when the regression uses an indicator for the worst months of bank returns, neither zombies nor non-zombies exhibit significant momentum in these months, and the difference between them is not statistically significant. This pattern is consistent with asymmetry in momentum returns. Daniel and Moskowitz (2016) show that momentum returns are negatively skewed and prone to crashes, particularly during bear markets when conditions recover and past losers rebound.

4 Conclusion

Zombie firms, a byproduct of persistent credit distortions, significantly affect asset pricing premiums in Japan, causing value and momentum factors to diverge from their international counterparts. Decades of subsidized credit to firms have weakened Japanese momentum and altered value premiums. Correcting for the influence of zombies realigns Japanese value and momentum premiums with global patterns and restores a positive price of risk for the Japanese momentum factor.

Zombies depress momentum in Japan. Without accounting for these firms, Japanese momentum is weak due to the high bank beta of zombie losers, whose returns decline sharply during periods of strong bank performance. These credit distortions are rooted in bank lending relationships. Firms reliant on forbearance-prone lenders show more severe asset pricing distortions than those with internationally oriented lenders, underscoring the role of credit distortions in reshaping long-run asset pricing dynamics.

that the zombie factor does not load negatively on past returns as we would expect for return reversals; if anything, it weakly loads positively on past returns.

References

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

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 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*, 2013.

Ryan Banerjee and Boris Hofmann. Corporate zombies: anatomy and life cycle. *Economic Policy*, page 757–803, 2022.

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

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

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

Mark M. Carhart. On Persistence in Mutual Fund Performance. *Journal of Finance*, 52(1): 57–82, 1997.

Kent Daniel and Tobias J. Moskowitz. Momentum Crashes. *Journal of Financial Economics*, 122(2):221–247, 2016.

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

Eugene F. Fama and Kenneth R. French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56, 1993.

Eugene F. Fama and Kenneth R. French. Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 105(3):457–472, 2012.

John M. Griffin, Xiuqing Ji, and J. Spencer Martin. Momentum Investing and Business Cycle Risk: Evidence from Pole to Pole. *Journal of Finance*, 58(6):2515–2547, 2003.

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

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.

Kewei Hou, Chen Xue, and Lu Zhang. Digesting Anomalies: An Investment Approach. *The Review of Financial Studies*, 28(3):650–705, 2015.

Narasimhan Jegadeesh. Evidence of Predictable Behavior of Security Returns. *Journal of Finance*, 45(3):881–898, 1990.

Josef Lakonishok, Andrei Shleifer, and Robert W. VISHNY. Contrarian Investment, Extrapolation, and Risk. *Journal of Finance*, 49(5):1541–1578, 1994.

Olivier Ledoit and Michael Wolf. Robust performance hypothesis testing with the sharpe ratio. *Journal of Empirical Finance*, 15(5):850–859, 2008.

Bruce N. Lehmann. Fads, Martingales, and Market Efficiency. *Quarterly Journal of Economics*, 105(1):1–28, 1990.

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.

Sharon Y. Ross. Government Risk Distortions. *Working Paper*, 2021.

K. Geert Rouwenhorst. International Momentum Strategies. *Journal of Finance*, 53(1):267–284, 2002.

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

5 Tables

	Momentum				Value		
	Total	Crisp	Fuzzy		Total	Crisp	Fuzzy
Full Data							
P1 (Losers)	57	46	11	P1 (Growth)	51	41	10
P2	56	46	10	P2	57	46	11
P3 (Winners)	54	43	11	P3 (Value)	59	48	11
Drop Crisp Zombies							
P1 (Losers)	26	0	26	P1 (Growth)	21	0	21
P2	25	0	25	P2	25	0	25
P3 (Winners)	24	0	24	P3 (Value)	28	0	28
Drop Crisp and Fuzzy Zombies							
P1 (Losers)	0	0	0	P1 (Growth)	0	0	0
P2	0	0	0	P2	0	0	0
P3 (Winners)	0	0	0	P3 (Value)	0	0	0

Table 1: Average Percentage of Zombies. Table shows the average percent of zombies in each tercile of the value and momentum sorts for three datasets: the full data, dropping crisp zombies, and dropping crisp and fuzzy zombies. P1 refers to the lowest tercile, and P3 is the highest tercile.

	P1 (Losers)	P3 (Winners)	Momentum Premium
Full Data	4.52	5.46	0.91
Drop Crisp Zombies	5.03	6.72	1.62
Drop Crisp and Fuzzy Zombies	4.83	7.95	2.99

	P1 (Growth)	P3 (Value)	Value Premium
Full Data	-0.22	11.12	11.36
Drop Crisp Zombies	1.08	11.38	10.20
Drop Crisp and Fuzzy Zombies	2.22	10.54	8.16

Table 2: Components of Value and Momentum Premiums. Table shows value-weighted portfolio returns for three samples: the full data, dropping crisp zombies, and dropping crisp and fuzzy zombies. P1 refers to the lowest tercile, and P3 is the highest tercile.

Dataset	Full Data	Drop Crisp Zombies	Drop Crisp + Fuzzy Zombies	Random Half	Random Other Half
Momentum Premium					
Mean	0.91	1.62	2.99	1.32	1.33
(t-statistic)	(0.33)	(0.56)	(1.01)	(0.46)	(0.46)
Std Dev	18.24	19.06	19.67	19.02	19.41
Sharpe	0.05	0.08	0.15	0.07	0.07
α	0.19	0.27	0.44	0.28	0.20
(p-value)	(0.40)	(0.27)	(0.09)	(0.25)	(0.41)
Momentum Strategy					
Mean	0.82	1.32	2.18	0.77	0.81
(t-statistic)	(0.34)	(0.54)	(0.87)	(0.32)	(0.33)
Std Dev	15.93	16.36	16.65	16.24	16.27
Sharpe	0.05	0.08	0.13	0.05	0.05
α	0.25	0.31	0.40	0.26	0.24
(p-value)	(0.23)	(0.16)	(0.08)	(0.21)	(0.28)
Value Premium					
Mean	11.36	10.20	8.16	10.57	10.50
(t-statistic)	(4.82)	(4.24)	(3.32)	(4.37)	(4.13)
Std Dev	15.05	15.42	15.90	15.45	16.27
Sharpe	0.76	0.66	0.51	0.68	0.65
α	0.83	0.74	0.57	0.81	0.78
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Value Strategy					
Mean	9.76	9.70	8.22	9.80	9.73
(t-statistic)	(4.66)	(4.30)	(3.49)	(4.74)	(4.29)
Std Dev	13.46	14.48	15.23	13.29	14.56
Sharpe	0.72	0.67	0.54	0.74	0.67
α	0.78	0.79	0.66	0.75	0.81
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 3: 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.

	Premium	Strategy
Full Data (VME)	-0.58	-0.62
Full Data	-0.57	-0.62
Drop Crisp Zombies	-0.58	-0.62
Drop Crisp and Fuzzy Zombies	-0.59	-0.60

Table 4: Value and Momentum Correlation. Table shows correlations 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. (2013) that are available on the AQR website.

	Mean p-value	Sharpe Ratio p-value
MOMENTUM PREMIUM		
Full Data = Drop Crisp + Fuzzy	0.04	0.09
Full Data = Drop Crisp	0.21	0.45
Full Data = Random Half	0.31	0.66
MOMENTUM STRATEGY		
Full Data = Drop Crisp + Fuzzy	0.02	0.08
Full Data = Drop Crisp	0.15	0.33
Full Data = Random Half	0.50	0.96
VALUE PREMIUM		
Full Data = Drop Crisp + Fuzzy	0.00	0.01
Full Data = Drop Crisp	0.10	0.16
Full Data = Random Half	0.16	0.05
VALUE STRATEGY		
Full Data = Drop Crisp + Fuzzy	0.03	0.01
Full Data = Drop Crisp	0.45	0.20
Full Data = Random Half	0.48	0.21

Table 5: Comparison of Japanese Value and Momentum. Table presents the p-values from statistical tests comparing the mean and Sharpe ratios. Means are tested using a t-test, and Sharpe ratios are tested using methodology from Ledoit and Wolf (2008).

	Mean				Sharpe Ratio			
	Momentum Premium	Momentum Strategy	Value Premium	Value Strategy	Momentum Premium	Momentum Strategy	Value Premium	Value Strategy
International								
US	3.69	5.69	0.19	1.96	0.25	0.36	0.01	0.13
Europe	5.46	6.86	1.41	2.65	0.39	0.53	0.12	0.25
UK	7.70	8.57	2.33	3.29	0.47	0.55	0.16	0.23
Global Average	5.62	7.04	1.31	2.63	0.37	0.48	0.10	0.20
Global Factor		5.62		3.77		0.46		0.34
Japan								
Full Data	0.60	0.53	10.64	9.62	0.03	0.03	0.71	0.71
Drop Crisp	1.31	1.05	9.38	9.51	0.07	0.06	0.61	0.65
Drop Crisp Fuzzy	2.79	1.96	7.22	7.95	0.14	0.12	0.46	0.52
Japan vs International								
Ratio (relative to Global Average)								
Full Data	0.11×	0.08×	8.13×	3.65×	0.09×	0.07×	7.11×	3.51×
Drop Crisp Zombies	0.23×	0.15×	7.16×	3.61×	0.19×	0.13×	6.11×	3.22×
Drop Crisp and Fuzzy Zombies	0.50×	0.28×	5.52×	3.02×	0.38×	0.24×	4.56×	2.56×
Ratio (relative to Global Factor)								
Full Data		0.09×		2.55×		0.07×		2.08×
Drop Crisp Zombies		0.19×		2.52×		0.14×		1.91×
Drop Crisp and Fuzzy Zombies		0.35×		2.11×		0.25×		1.52×

Table 6: Global Comparison of Value and Momentum. Table presents the annualized average return percent and the Sharpe ratio for the value and momentum premium and value and momentum strategy factors internationally. Japan's factors are also calculated with zombies removed. International data are from the AQR website, including The Global Average (calculated as the equal-weighted average of the U.S., U.K., and Europe values) and the Global Strategy Factor. Ratios compare Japan to the the Global Average or Factor. Statistics are computed from monthly returns and reported as annualized numbers.

	Mean p-value	Sharpe Ratio p-value
Momentum Premium		
Global Average = Drop Crisp + Fuzzy	0.35	0.15
Global Average = Drop Crisp	0.14	0.06
Global Average = Full	0.07	0.03
Momentum Strategy		
Global Average = Drop Crisp + Fuzzy	0.05	0.04
Global Average = Drop Crisp	0.02	0.01
Global Average = Full	0.01	0.01
Value Premium		
Global Average = Drop Crisp + Fuzzy	0.02	0.05
Global Average = Drop Crisp	0.00	0.01
Global Average = Full	0.00	0.00
Value Strategy		
Global Average = Drop Crisp + Fuzzy	0.02	0.15
Global Average = Drop Crisp	0.00	0.04
Global Average = Full	0.00	0.02

Table 7: Comparison to Global Value and Momentum. Table presents the p-values from statistical tests comparing the mean and Sharpe ratios. Means are tested using a t-test, and Sharpe ratios are tested using methodology from Ledoit and Wolf (2008).

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
MOMENTUM					
Mean	1.50	−1.94	2.62	1.16	2.06
(t-stat)	(0.45)	(−0.44)	(0.71)	(0.34)	(0.61)
Std Dev	16.92	22.33	18.37	17.43	17.07
Sharpe	0.09	−0.09	0.14	0.07	0.12
VALUE					
Mean	9.47	12.25	8.08	9.62	5.46
(t-stat)	(2.92)	(2.72)	(2.35)	(3.07)	(1.55)
Std Dev	15.78	21.63	16.81	15.23	17.41
Sharpe	0.60	0.57	0.48	0.63	0.31

Table 8: 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. (2013), 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	1.014	0.027	0.192	0.044	0.449	-0.020	0.242	0.076	0.317	0.064	0.339
	(1.52)	(0.05)	(0.33)	(0.07)	(0.75)	(-0.03)	(0.40)	(0.13)	(0.53)	(0.11)	(0.57)
	(1.45)	(0.05)	(0.30)	(0.07)	(0.63)	(-0.03)	(0.33)	(0.12)	(0.44)	(0.10)	(0.47)
$Mkt - Rf$	-0.817	0.079	-0.049	0.059	-0.276	0.123	-0.069	0.026	-0.161	0.038	-0.179
	(-1.10)	(0.13)	(-0.08)	(0.09)	(-0.43)	(0.18)	(-0.10)	(0.04)	(-0.25)	(0.06)	(-0.28)
	(-1.05)	(0.12)	(-0.07)	(0.08)	(-0.37)	(0.17)	(-0.09)	(0.04)	(-0.21)	(0.06)	(-0.23)
SMB		0.080	0.083	0.071	0.078	0.073	0.079	0.071	0.085	0.072	0.085
		(0.52)	(0.54)	(0.46)	(0.51)	(0.47)	(0.52)	(0.46)	(0.55)	(0.47)	(0.55)
		(0.52)	(0.54)	(0.46)	(0.51)	(0.47)	(0.52)	(0.46)	(0.56)	(0.46)	(0.56)
HML		0.369	0.373								
		(2.34)	(2.36)								
		(2.36)	(2.38)								
WML			1.126								
			(1.87)								
			(1.75)								
HML_{ZA}				0.651	-0.252	0.704	-0.131	0.586	-0.231	0.592	-0.261
				(2.15)	(-0.77)	(2.15)	(-0.38)	(2.24)	(-0.76)	(2.22)	(-0.84)
				(2.17)	(-0.69)	(2.16)	(-0.34)	(2.26)	(-0.73)	(2.24)	(-0.79)
WML_{ZA}					1.887		1.875		1.756		1.863
					(3.03)		(2.89)		(2.74)		(2.86)
					(2.60)		(2.47)		(2.47)		(2.50)
Ann. R.P. ↑			0.54		2.63		2.22		2.72		2.80
TS GRS p-value	0.05	0.15	0.19	0.05	0.03	0.08	0.10	0.02	0.00	0.04	0.01
MAPE (%)	0.14	0.10	0.09	0.11	0.10	0.11	0.10	0.11	0.12	0.11	0.12
TS Avg R^2	0.77	0.92	0.92	0.91	0.91	0.91	0.91	0.91	0.92	0.91	0.91
Quarters (T)	405	405	405	405	405	405	405	405	405	405	405
Portfolios (N)	25	25	25	25	25	25	25	25	25	25	25

Table 9: 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
$Mkt - Rf$	0.309		0.144	-0.433	-0.285
	(1.22)		(1.73)	(-5.18)	(-4.60)
SMB	0.032	0.051		0.036	-0.051
	(0.21)	(1.73)		(0.70)	(-1.35)
HML	0.390	-0.145	0.034		-0.197
	(2.68)	(-5.18)	(0.70)		(-5.57)
WML	0.232	-0.176	-0.088	-0.365	
	(1.16)	(-4.60)	(-1.35)	(-5.57)	

Panel B: Zombie-Adjusted Factors, Drop Crisp Zombies

	Intercept	$Mkt - Rf$	SMB	HML_{ZA}	WML_{ZA}
$Mkt - Rf$	0.400		0.127	-0.332	-0.293
	(1.52)		(1.49)	(-4.25)	(-3.96)
SMB	0.090	0.043		-0.052	-0.086
	(0.58)	(1.49)		(-1.12)	(-1.96)
HML_{ZA}	0.781	-0.130			-0.627
	(4.86)	(-4.25)	(-1.12)		(-17.66)
WML_{ZA}	0.638	-0.128	-0.110	-0.698	
	(3.72)	(-3.96)	(-1.96)	(-17.66)	

Panel C: Zombie-Adjusted Factors, Drop Crisp and Fuzzy Zombies

	Intercept	$Mkt - Rf$	SMB	HML_{ZA}	WML_{ZA}
$Mkt - Rf$	0.394		0.140	-0.334	-0.262
	(1.50)		(1.65)	(-4.45)	(-3.70)
SMB	0.071	0.048		-0.028	-0.057
	(0.46)	(1.65)		(-0.62)	(-1.34)
HML_{ZA}	0.759	-0.141	-0.035		-0.611
	(4.55)	(-4.45)	(-0.62)		(-17.20)
WML_{ZA}	0.664	-0.126	-0.079	-0.695	
	(3.70)	(-3.70)	(-1.34)	(-17.20)	

Panel D: Zombie-Adjusted Factors, Triple-Sort Crisp Zombies

	Intercept	$Mkt - Rf$	SMB	HML_{ZA}	WML_{ZA}
$Mkt - Rf$	0.506		0.150	-0.442	-0.409
	(1.94)		(1.80)	(-5.41)	(-5.38)
SMB	0.024	0.053		0.026	-0.030
	(0.16)	(1.80)		(0.52)	(-0.64)
HML_{ZA}	0.829	-0.154	0.026		-0.611
	(5.57)	(-5.41)	(0.52)		(-17.47)
WML_{ZA}	0.656	-0.165	-0.034	-0.708	
	(4.02)	(-5.38)	(-0.64)	(-17.47)	

Panel E: Zombie-Adjusted Factors, Triple-Sort Crisp and Fuzzy Zombies

	Intercept	$Mkt - Rf$	SMB	HML_{ZA}	WML_{ZA}
$Mkt - Rf$	0.483		0.145	-0.433	-0.387
	(1.86)		(1.73)	(-5.30)	(-5.12)
SMB	0.040	0.051		0.010	-0.041
	(0.26)	(1.73)		(0.19)	(-0.88)
HML_{ZA}	0.790	-0.151	0.010		-0.610
	(5.29)	(-5.30)	(0.19)		(-17.67)
WML_{ZA}	0.648	-0.159	-0.047	-0.717	
	(3.95)	(-5.12)	(-0.88)	(-17.67)	

Table 10: Spanning Tests for Zombie-Adjusted Factors. Table presents time-series regressions at the monthly level. Each row is a regression result that tests if the factor in the left column is spanned by the 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 zombies or triple-sorting zombies. t-statistics are reported in parentheses.

6 Figures

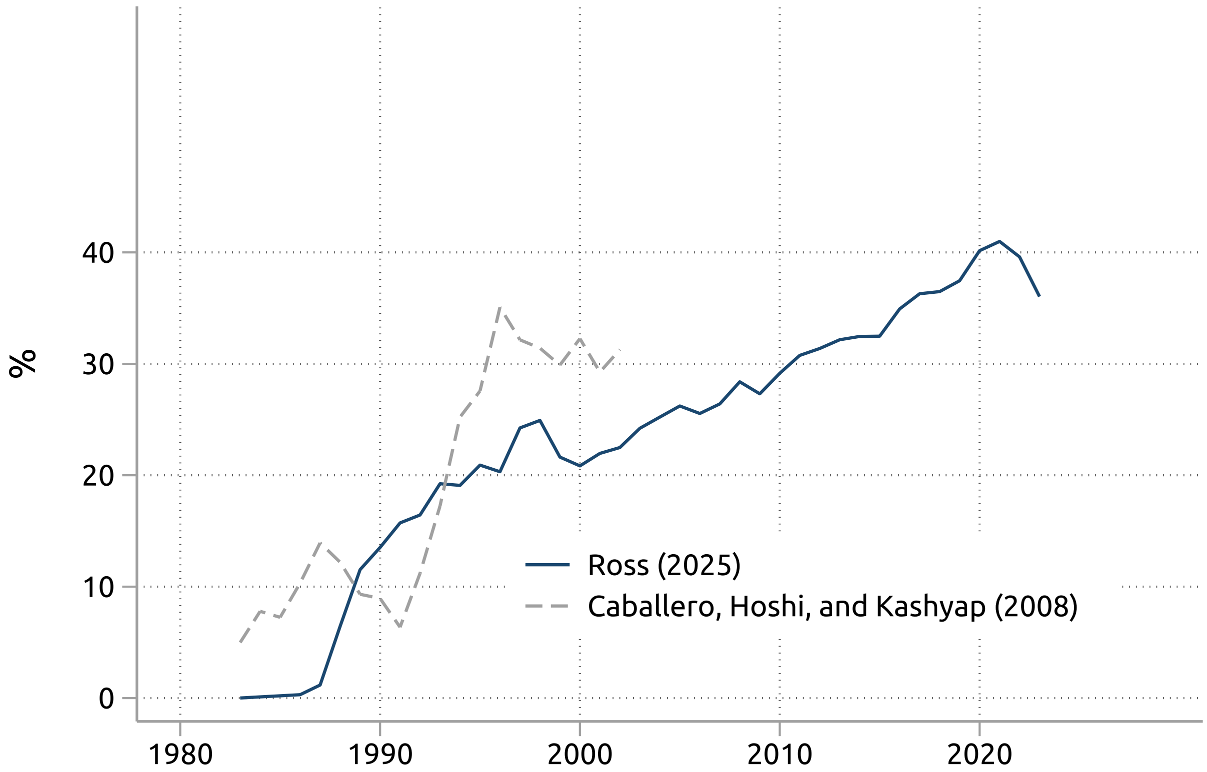

Figure 1: Percentage of Zombie Firms in Japan. Figure compares the percentage of Japanese zombies in the data and the zombie percentage from Caballero et al. (2008). This graph plots the share of crisp zombies in the raw dataset (before restricting to the liquid sample) to be directly comparable to Caballero et al. (2008)'s figure, which uses a 0% cutoff. Zombies are identified on a monthly basis, and the plotted percentage is the annual average.

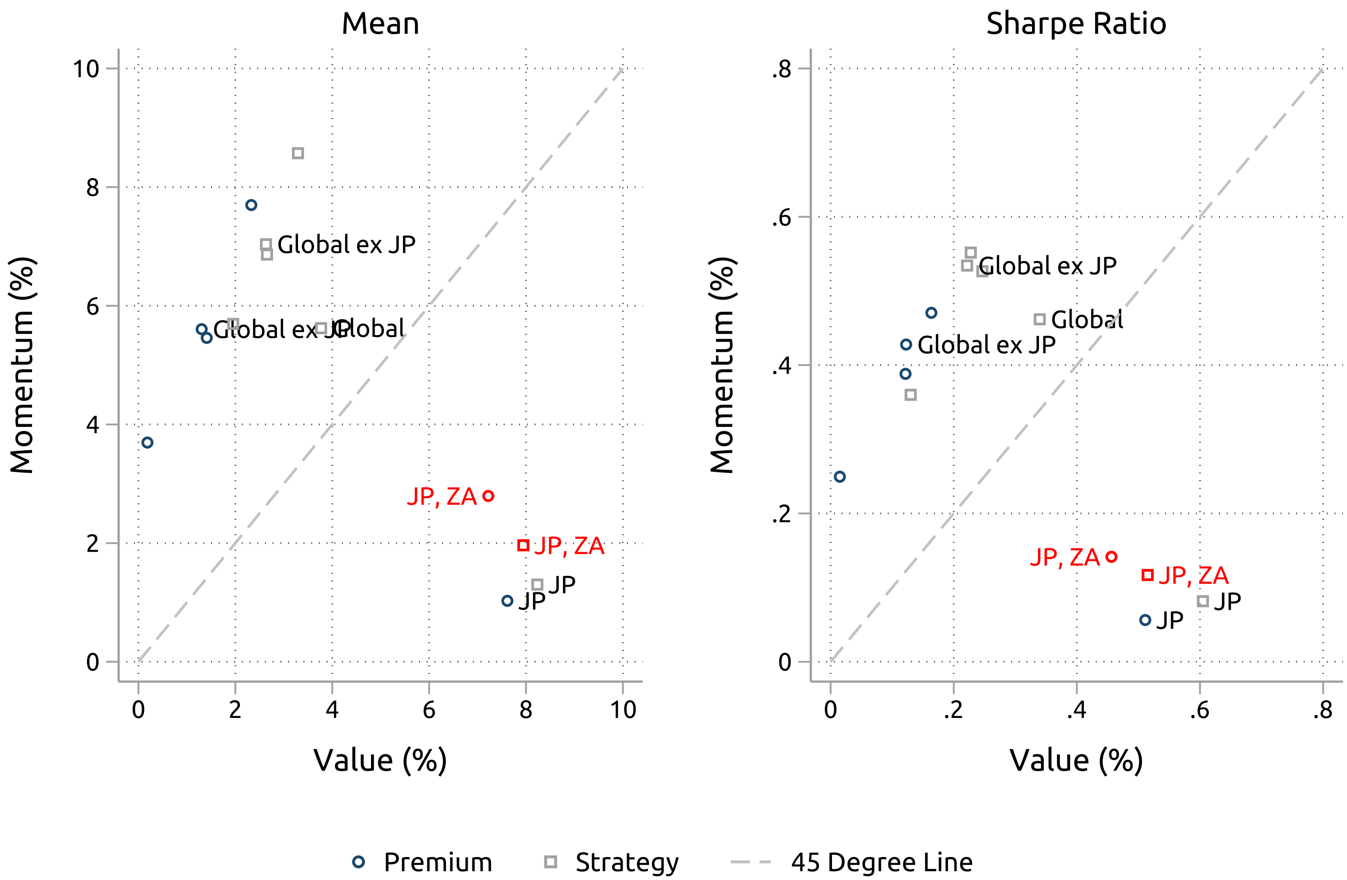

Figure 2: Global Comparison of Value and Momentum. Figure shows the average returns and Sharpe ratios for value and momentum premiums and strategies in the U.S., Europe, U.K., and Japan. See the text for details on the factors' construction. Left panel plots the average returns, and right panel plots the Sharpe ratio. International statistics are calculated using data from the AQR website. Statistics are computed from monthly returns and reported as annualized numbers.

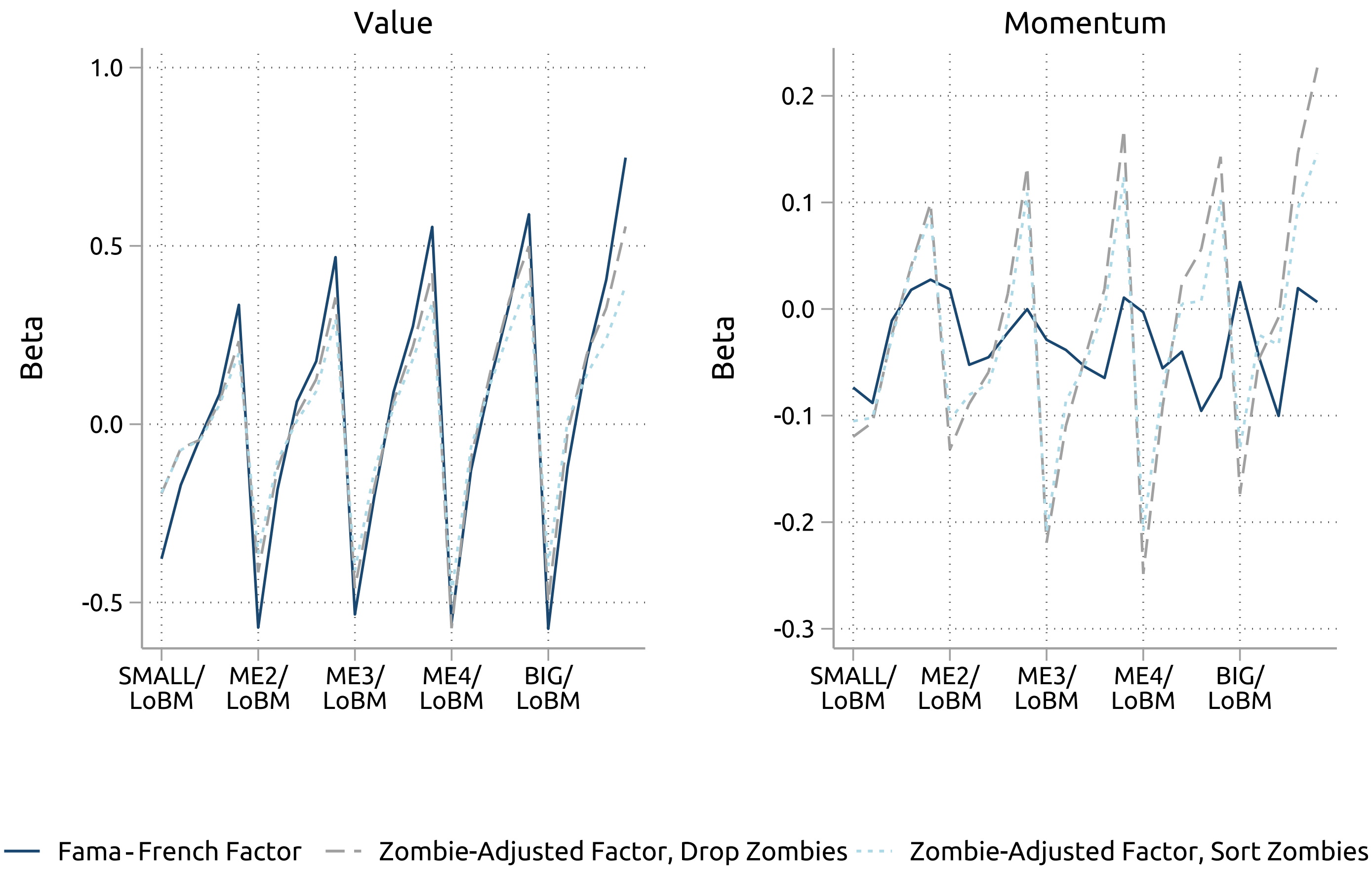

Figure 3: Value and Momentum Betas. Figure shows the betas of the 25 Fama–French portfolios to value and momentum factors. Betas are estimated using the four-factor model. Left panel plots betas to the value factors, HML and HML_{ZA}. Right panel plots betas to the momentum factors, WML and WML_{ZA}. Zombie-adjusted factors, HML_{ZA} and WML_{ZA}, are constructed by dropping zombies and triple-sorting zombies.

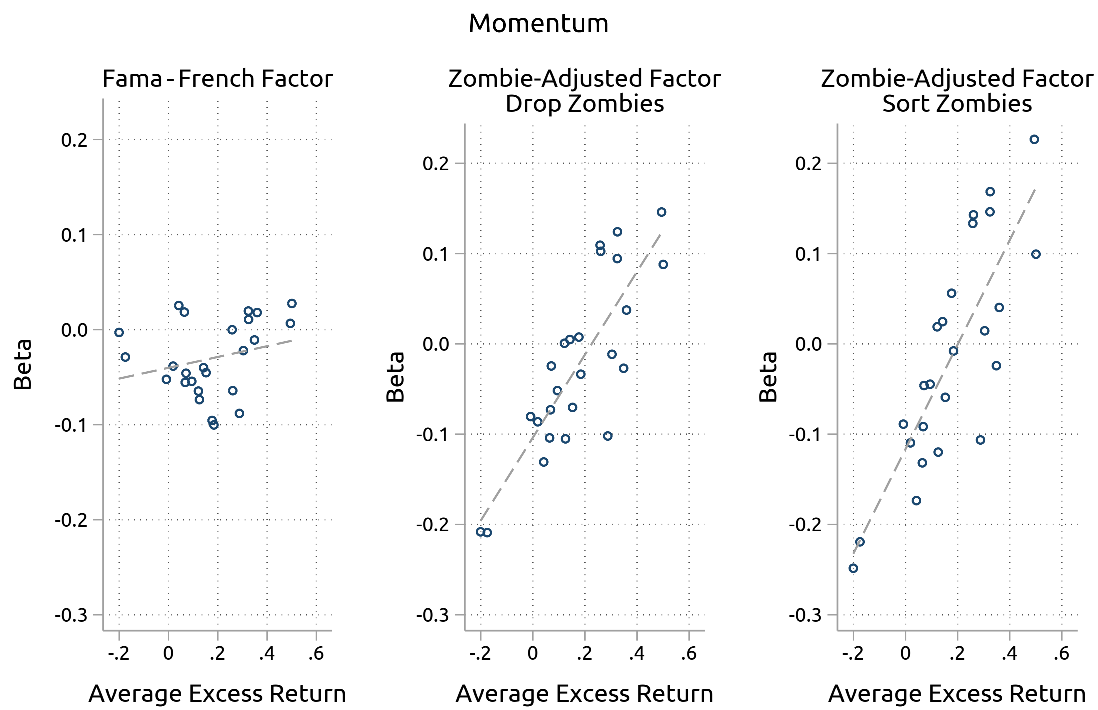

Figure 4: Securities Market Line for Momentum. Figure shows the betas of the 25 Fama–French portfolios to the momentum factors and the portfolios' expected returns. Betas are estimated using the four-factor model, and figure plots betas to the momentum factors, WML and WML_{ZA}. The zombie-adjusted factor, WML_{ZA}, is formed by dropping zombies and triple-sorting zombies.

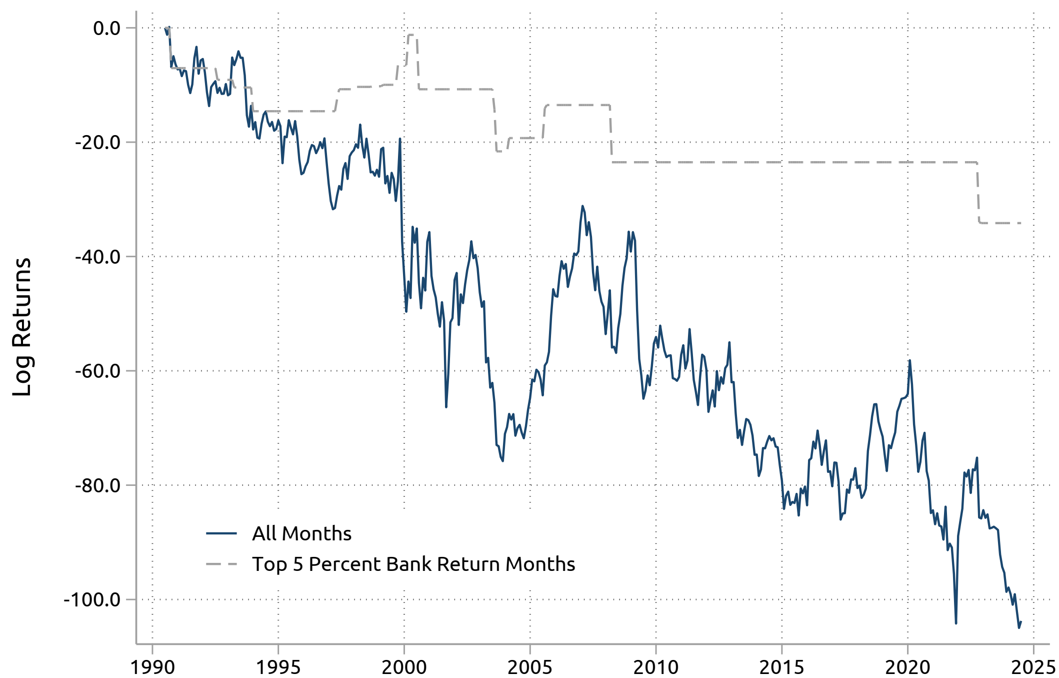

Figure 5: Cumulative Difference in Zombie and Non-zombie Momentum

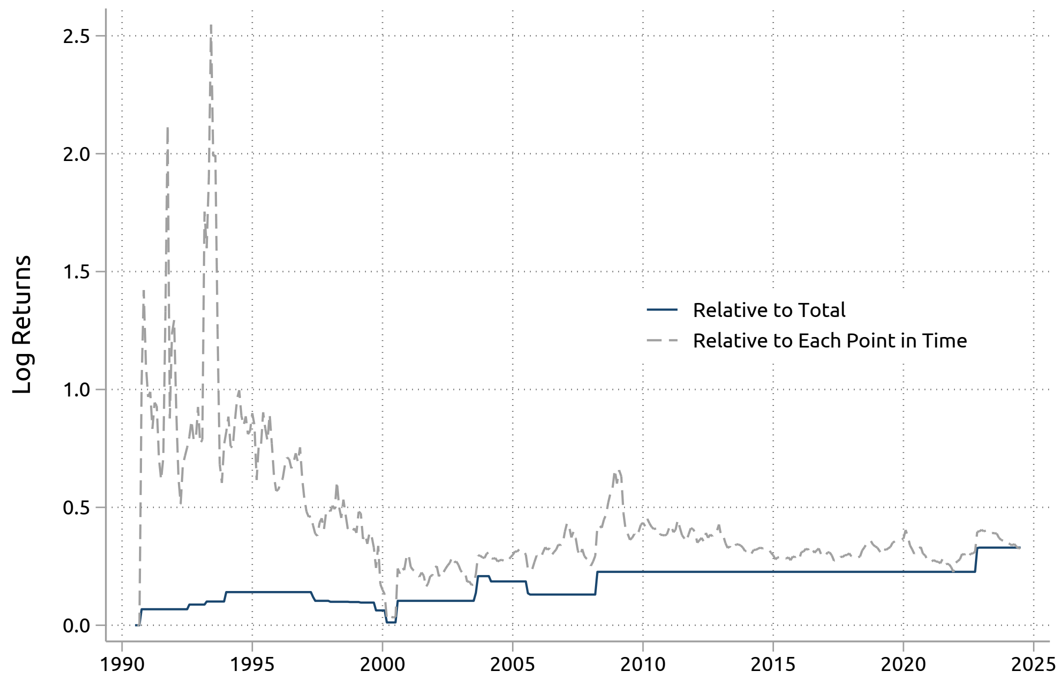

Figure 6: Contribution of Months with Top 5 Percent of Bank Returns, Relative to Cumulative Difference

Appendix

A Alternative Factors

In this section, I consider the inclusion of other factors and adjustments to the zombie-ness factor. The results show that the zombie-adjusted factors constructed in Section 2 and tested in Section 3 robustly earn compensation for risk and are consistently unspanned by the inclusion of other factors.

First, I consider an alternative construction to WML_{ZA} and HML_{ZA}, the zombie-adjusted factor-mimicking portfolios from Section 2 control for zombies by including zombie portfolios in the long and short legs. The method in Section 2 to construct WML_{ZA} and HML_{ZA} follows the process of Fama and French (1993) to create factors that are largely free of the influence of zombies. Now, I consider an alternative construction that only includes zombie portfolios in the long leg (and only considers non-zombie portfolios in the short leg). Such factors would be implicitly long zombies and short zombies.

As before, I form triple-sorted portfolios. 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 proposed factors:

$$HML^{alt}_{ZA} = \frac{\text{H/S/Z} + \text{H/B/Z}}{2} - \frac{\text{L/S/N} + \text{L/B/N}}{2} \tag{13}$$

and

$$WML^{alt}_{ZA} = \frac{\text{W/S/Z} + \text{W/B/Z}}{2} - \frac{\text{L/S/N} + \text{L/B/N}}{2}. \tag{14}$$

Table A.7 shows spanning tests using these alternative momentum and value factors. Each value in this table is an intercept or intercept t-statistic of a spanning test; the row labels the dependent variable in the regression, and the factors in the same panel are the regressors. For example, the first value in the table is the intercept in a regression of the market factor on th SMB, HML^{alt}_{ZA}, and WML^{alt}_{ZA} factors, where the zombie-adjusted factors are created by triple-sorting on crisp and zombies.

The insignificant coefficient on WML^{alt}_{ZA} points to the exclusion of a momentum factor that is long zombies from the model. This is consistent with my results: momentum in Japan earns significant compensation for risk and is significantly higher only after controlling for zombies.

The zombie-adjusted factors constructed in Section 2 remove zombies or control for zombies by having the long and short legs cancel out. They are factor-mimicking portfolios that proxy a counterfactual world in which zombies do not exist and affect momentum. The alternative factors reflect two factors: they are long zombies and they are long the original factor (value or momentum). Hence, they likely load on zombie risk more than the unadjusted factors, and they have similar results to the standard Japanese momentum factor. The insignificant intercept in the spanning test shows that momentum that is long zombies should not be included in the model.

Second, one concern is that a factor related to zombie-ness should be included in the model. I show that a zombie return factor is unspanned by the other other factors, but that the inclusion of a zombie return factor does not change the cross-sectional results in Section 3.

I construct a zombie factor that is the excess return of zombie firms over the risk-free rate ($Zombie$) and a zombie-minus-non-zombie factor ($Zombie - Non\text{-}zombie$) that is long zombies and short non-zombies. I include these factors in the spanning tests in Table A.7 [N.B. shown above]. In panel A, columns 2 and 3 show that the zombie factors have significant negative coefficients. This means that the zombie factor cannot be explained by the standard, unadjusted factors. And also importantly, the standard momentum factor WML remains spanned by the other factors. These results suggest that unadjusted momentum should not be included in an asset pricing model for Japan.

Panels B and C use the zombie factor or zombie-minus-non-zombie factor coupled with zombie-adjusted momentum and value factors in the spanning tests. The zombie factors again have significant coefficients, and zombie-adjusted momentum is unspanned by the other factors. The results suggest that a zombie factor could be included in the model and, importantly, are consistent with the results in Section 3: the momentum factor is unspanned only after adjusting for zombies.

Table A.8 adds the zombie factor and zombie minus non-zombie factor separately to the cross-sectional regression. The results show that the zombie factor has marginally significant prices of risk using GMM standard errors, and the zombie minus non-zombie factor is insignificant. In general, the inclusion of these factors does not change the significance of the zombie-adjusted momentum results, and this further supports that momentum earns significant compensation for risk after adjusting for zombies.

Some potential concerns with the cross-sectional and spanning results are that a zombie-ness factor should be included in the model or that the zombie-adjusted factors should be constructed differently. I discuss this further in the online appendix and show that these zombie-adjusted factors—constructed by either removing zombies or triple-sorting to control for zombies—robustly earn compensation for risk and are consistently unspanned by other factors.

B Appendix Tables

	ROA	ROE	$\mathbb{I}$(Gross Profit Margin < 0)	$\mathbb{I}$(Net Profit Margin < 0)	$\mathbb{I}$(Operating Profit Margin < 0)
	(1)	(2)	(3)	(4)	(5)
$\mathbb{I}$(Zombie)	-0.648^{***}	-1.650^{***}	0.002^{**}	0.023^{***}	0.015^{***}
	(-9.58)	(-3.64)	(2.44)	(5.44)	(4.98)
N	28,671	28,644	29,596	29,596	29,596
Adj. R^2	0.49	0.12	0.08	0.18	0.16
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Table A.1: Zombies and Profitability. Table presents time-series regressions of firm profitability measures on an indicator variable for zombie firms. Regression uses annual data. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Fama–French Factors					
$Mkt-Rf$	0.464	$Mkt-Rf$	0.637	$Mkt-Rf$	0.307
	(1.90)		(3.05)		(1.21)
SMB	0.074	SMB	0.165	SMB	-0.016
	(0.48)		(1.10)		(-0.11)
HML	0.452	HML	0.532	HML	0.381
	(3.62)		(3.56)		(2.62)
WML	0.150	WML	0.119	WML	0.147
	(0.76)		(0.58)		(0.77)
RMW	0.220	QMJ	0.391	BAB	0.205
	(2.56)		(3.54)		(1.12)
Panel B: Zombie-adjusted Factors, Drop Crisp Zombies					
$Mkt-Rf$	0.566	$Mkt-Rf$	0.735	$Mkt-Rf$	0.424
	(2.21)		(3.44)		(1.61)
SMB	0.153	SMB	0.215	SMB	0.018
	(0.99)		(1.41)		(0.12)
HML_{ZA}	0.832	HML_{ZA}	0.885	HML_{ZA}	0.801
	(5.65)		(5.32)		(4.99)
WML_{ZA}	0.674	WML_{ZA}	0.659	WML_{ZA}	0.600
	(3.90)		(3.58)		(3.49)
RMW	0.274	QMJ	0.458	BAB	0.312
	(2.91)		(4.01)		(1.65)
Panel C: Zombie-adjusted Factors, Drop Crisp and Fuzzy Zombies					
$Mkt-Rf$	0.541	$Mkt-Rf$	0.677	$Mkt-Rf$	0.414
	(2.12)		(3.20)		(1.57)
SMB	0.125	SMB	0.181	SMB	0.010
	(0.81)		(1.20)		(0.07)
HML_{ZA}	0.805	HML_{ZA}	0.809	HML_{ZA}	0.772
	(5.22)		(4.63)		(4.62)
WML_{ZA}	0.690	WML_{ZA}	0.636	WML_{ZA}	0.622
	(3.82)		(3.28)		(3.47)
RMW	0.247	QMJ	0.413	BAB	0.270
	(2.61)		(3.58)		(1.43)
Panel D: Zombie-adjusted Factors, Triple Sort Crisp Zombies					
$Mkt-Rf$	0.704	$Mkt-Rf$	0.801	$Mkt-Rf$	0.516
	(2.78)		(3.75)		(1.97)
SMB	0.085	SMB	0.153	SMB	-0.033
	(0.54)		(0.99)		(-0.22)
HML_{ZA}	0.881	HML_{ZA}	0.924	HML_{ZA}	0.834
	(6.54)		(5.94)		(5.59)
WML_{ZA}	0.702	WML_{ZA}	0.634	WML_{ZA}	0.593
	(4.27)		(3.61)		(3.68)
RMW	0.320	QMJ	0.462	BAB	0.255
	(3.41)		(4.02)		(1.34)
Panel E: Zombie-adjusted Factors, Triple Sort Crisp and Fuzzy Zombies					
$Mkt-Rf$	0.672	$Mkt-Rf$	0.764	$Mkt-Rf$	0.496
	(2.66)		(3.58)		(1.90)
SMB	0.101	SMB	0.161	SMB	-0.019
	(0.64)		(1.05)		(-0.13)
HML_{ZA}	0.840	HML_{ZA}	0.866	HML_{ZA}	0.797
	(6.20)		(5.53)		(5.33)
WML_{ZA}	0.689	WML_{ZA}	0.616	WML_{ZA}	0.591
	(4.16)		(3.48)		(3.63)
RMW	0.303	QMJ	0.443	BAB	0.261
	(3.24)		(3.85)		(1.38)

Table A.2: 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	Zombie − Non-zombie
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Return	0.624***	0.559***	0.065***	0.351***	0.271***	0.080***
	(19.47)	(16.10)	(4.39)	(12.70)	(8.85)	(4.56)
Market Return				0.534***	0.564***	−0.030
				(18.32)	(17.45)	(−1.59)
N	409	409	409	409	409	409
Adj. R^2	0.52	0.43	0.03	0.75	0.69	0.04

Table A.3: Bank Beta for Zombies and Non-zombies. Table presents time-series regressions at the monthly level. The dependent variable is the *Zombie* factor, *Non-zombie* factor, and the difference betweent the two. Independent variables are the bank return and the market return. Intercept is included in each regression but omitted from the table, and regression includes year fixed effects. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Bank Beta

	Non-zombie Winners		Non-zombie Losers		Zombie Winners		Zombie Losers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank Return	0.548***	0.517***	0.692***	0.680***	0.577***	0.549***	0.747***	0.736***
	(12.99)	(12.17)	(18.30)	(17.14)	(15.72)	(14.74)	(20.08)	(18.97)
N	409	409	409	409	409	409	409	409
Adj. R^2	0.29	0.34	0.45	0.44	0.38	0.41	0.50	0.49
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	0.699***	0.668***	0.793***	0.799***	0.686***	0.664***	0.825***	0.828***
	(17.80)	(16.61)	(22.10)	(21.24)	(19.80)	(18.69)	(22.66)	(21.74)
N	409	409	409	409	409	409	409	409
Adj. R^2	0.44	0.47	0.54	0.55	0.49	0.52	0.56	0.56
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	0.258***	0.248***	0.392***	0.383***	0.309***	0.296***	0.447***	0.441***
	(5.95)	(5.72)	(10.78)	(10.20)	(8.40)	(8.00)	(12.61)	(12.12)
Market Return	0.551***	0.526***	0.568***	0.582***	0.509***	0.496***	0.568***	0.578***
	(12.20)	(11.48)	(14.97)	(14.70)	(13.28)	(12.71)	(15.36)	(15.06)
N	409	409	409	409	409	409	409	409
Adj. R^2	0.48	0.51	0.64	0.65	0.56	0.59	0.68	0.68
Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Table A.4: 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 and the market return. Intercept is included in each regression but omitted from the table. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Zombie - Non-zombie Momentum (1)	Zombie Momentum (2)	Non-zombie Momentum (3)	Zombie Winners (4)	Zombie Losers (5)	Non-zombie Winners (6)	Non-zombie Losers (7)
Panel A: Returns in Top Bank Return Months							
$\mathbb{I}$(Top Bank Return)	−1.900**	−3.940***	−2.040	9.849***	13.789***	9.782***	11.822***
	(−2.15)	(−3.47)	(−1.61)	(7.86)	(9.86)	(7.19)	(8.42)
N	409	409	409	409	409	409	409
Adj. R^2	-0.00	0.10	0.05	0.20	0.21	0.19	0.16
Panel B: Returns in Top Market Return Months							
	Zombie - Non-zombie Momentum (1)	Zombie Momentum (2)	Non-zombie Momentum (3)	Zombie Winners (4)	Zombie Losers (5)	Non-zombie Winners (6)	Non-zombie Losers (7)
$\mathbb{I}$(Top Market Return)	−0.280	−3.496***	−3.216**	8.223***	11.719***	7.980***	11.197***
	(−0.32)	(−3.12)	(−2.59)	(6.50)	(8.23)	(5.83)	(8.03)
N	409	409	409	409	409	409	409
Adj. R^2	-0.02	0.09	0.06	0.16	0.16	0.15	0.15
Panel C: Returns in Top Bank Return Months and Top Market Return Months							
	Zombie - Non-zombie Momentum (1)	Zombie Momentum (2)	Non-zombie Momentum (3)	Zombie Winners (4)	Zombie Losers (5)	Non-zombie Winners (6)	Non-zombie Losers (7)
$\mathbb{I}$(Top Bank Return)	−2.029**	−3.106***	−1.076	7.957***	11.063***	7.974***	9.050***
	(−2.16)	(−2.59)	(−0.80)	(6.13)	(7.78)	(5.63)	(6.35)
$\mathbb{I}$(Top Market Return)	0.384	−2.481**	−2.865**	5.620***	8.101***	5.373***	8.237***
	(0.42)	(−2.10)	(−2.17)	(4.40)	(5.78)	(3.85)	(5.86)
N	409	409	409	409	409	409	409
Adj. R^2	-0.01	0.11	0.06	0.23	0.27	0.21	0.23

Table A.5: 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. $\mathbb{I}$(Top Bank Return) = 1 if the month is a top 5 percent bank return month, and 0 otherwise. $\mathbb{I}$(Top Market Return) = 1 if the month is a top 5 percent market return month, and 0 otherwise. Intercept is included in each regression but omitted from the table. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Zombies$_t$			Zombie Losers$_t$		
	(1)	(2)	(3)	(4)	(5)	(6)
Zombies$_{t-1}$	0.040	0.041	0.027			
	(0.80)	(0.82)	(0.56)			
Zombies$_{t-2}$		−0.038	−0.043			
		(−0.78)	(−0.88)			
Zombies$_{t-3}$			0.117**			
			(2.40)			
Zombie Losers$_{t-1}$				0.038	0.039	0.030
				(0.76)	(0.78)	(0.60)
Zombie Losers$_{t-2}$					−0.052	−0.055
					(−1.05)	(−1.11)
Zombie Losers$_{t-3}$						0.052
						(1.07)
N	408	407	406	408	407	406
Adj. R^2	-0.00	-0.00	0.01	-0.00	-0.00	-0.00

Table A.6: Zombie and Zombie Loser Reversal. Table presents the regression of the zombie factor and zombie loser portfolio on past returns. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Triple Sorted Alternative Factor and Zombie-Related Factors

$Mkt - Rf$	0.273	$Mkt - Rf$	0.210	$Mkt - Rf$	0.386
	(1.05)		(3.94)		(1.52)
SMB	0.023	SMB	-0.029	SMB	0.026
	(0.15)		(-0.19)		(0.17)
HML_{ZA}^{alt}	0.578	HML	0.331	HML	0.462
	(3.05)		(2.24)		(3.32)
WML_{ZA}^{alt}	0.327	WML	0.246	WML	0.102
	(1.80)		(1.22)		(0.52)
		$Zombie$	-0.200	$Zombie - Non\text{-}zombie$	-0.211
			(-3.76)		(-2.57)

Panel B: Zombie-Adjusted Factors and Zombie Factor

Zombie-Adjustment for HML_{ZA} and WML_{ZA}	Drop Crisp Zombies	Drop Crisp and Fuzzy Zombies	Triple-Sort Crisp Zombies	Triple-Sort Crisp and Fuzzy Zombies
	Intercept	Intercept	Intercept	Intercept
$Mkt - Rf$	0.196	0.200	0.188	0.190
	(3.61)	(3.70)	(3.45)	(3.49)
SMB	0.027	0.009	-0.028	-0.015
	(0.17)	(0.06)	(-0.18)	(-0.10)
HML_{ZA}	0.702	0.681	0.737	0.697
	(4.31)	(4.02)	(4.91)	(4.63)
WML_{ZA}	0.596	0.629	0.613	0.605
	(3.42)	(3.44)	(3.71)	(3.64)
$Zombie$	-0.182	-0.186	-0.169	-0.171
	(-3.36)	(-3.45)	(-3.11)	(-3.16)

Panel C: Zombie-Adjusted Factors and Zombie-Non-zombie Factor

Zombie-Adjustment for HML_{ZA} and WML_{ZA}	Drop Crisp Zombies	Drop Crisp and Fuzzy Zombies	Triple-Sort Crisp Zombies	Triple-Sort Crisp and Fuzzy Zombies
$Mkt - Rf$	0.509	0.490	0.593	0.572
	(1.93)	(1.87)	(2.27)	(2.19)
SMB	0.096	0.076	0.022	0.038
	(0.62)	(0.49)	(0.14)	(0.24)
HML_{ZA}	0.858	0.826	0.886	0.847
	(5.57)	(5.11)	(6.09)	(5.82)
WML_{ZA}	0.624	0.636	0.613	0.607
	(3.58)	(3.50)	(3.72)	(3.65)
$Zombie - Non\text{-}zombie$	-0.262	-0.234	-0.252	-0.246
	(-3.10)	(-2.76)	(-2.92)	(-2.86)

Table A.7: Spanning Tests with Alternative Factors. Table presents the intercepts and t-statistics from monthly time-series regressions of each factor on the other factors in the same column and panel. For example, the first coefficient is the intercept from the regression of the market factor on SMB, HML_{ZA}^{alt}, and WML_{ZA}^{alt}. The last coefficient is the intercept from the regression of $Zombie - Non\text{-}zombie$ 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.

Prices of Risk: $\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f$								
	Drop Crisp		Drop Crisp + Fuzzy		Triple-Sort Crisp		Triple-Sort Crisp + Fuzzy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(1.84)	(1.47)	(1.7)	(1.45)	(1.62)	(1.24)	(1.67)	(1.35)
$Mkt - Rf$	-1.228	-0.847	-1.159	-0.843	-1.137	-0.693	-1.155	-0.765
	(-1.96)	(-1.35)	(-1.83)	(-1.35)	(-1.79)	(-1.1)	(-1.83)	(-1.22)
	(-1.53)	(-1.13)	(-1.41)	(-1.12)	(-1.35)	(-0.93)	(-1.38)	(-1.02)
SMB	0.077	0.041	0.077	0.037	0.085	0.046	0.084	0.044
	(0.50)	(0.27)	(0.50)	(0.24)	(0.55)	(0.30)	(0.55)	(0.28)
	(0.50)	(0.26)	(0.50)	(0.24)	(0.55)	(0.29)	(0.55)	(0.28)
HML_{ZA}	-0.501	-0.155	-0.429	-0.159	-0.408	-0.142	-0.418	-0.172
	(-1.46)	(-0.48)	(-1.20)	(-0.46)	(-1.32)	(-0.47)	(-1.34)	(-0.57)
	(-1.04)	(-0.47)	(-0.85)	(-0.47)	(-0.92)	(-0.49)	(-0.94)	(-0.58)
WML_{ZA}	2.101	1.342	2.118	1.358	2.094	1.161	2.142	1.252
	(3.33)	(2.28)	(3.21)	(2.14)	(3.25)	(1.76)	(3.27)	(1.93)
	(2.21)	(1.91)	(2.13)	(1.85)	(2.08)	(1.68)	(2.12)	(1.72)
Zombie	-1.817		-1.768		-1.767		-1.773	
	(-2.52)		(-2.43)		(-2.42)		(-2.45)	
	(-1.93)		(-1.85)		(-1.77)		(-1.88)	
Zombie $-$ *Non-zombie*		0.498		0.542		0.502		0.520
		(1.58)		(1.78)		(1.37)		(1.58)
		(1.49)		(1.65)		(1.25)		(1.37)
Ann. R.P. ↑	2.90	1.87	2.49	1.63	3.25	1.84	3.22	1.92
TS GRS p-value	0.06	0.04	0.21	0.11	0.01	0.01	0.02	0.02
MAPE (%)	0.10	0.11	0.09	0.11	0.12	0.13	0.11	0.12
TS Avg R^2	0.91	0.91	0.91	0.91	0.92	0.92	0.92	0.92
Quarters (T)	405	405	405	405	405	405	405	405
Portfolios (N)	25	25	25	25	25	25	25	25

Table A.8: Cross-Sectional Regressions with Zombie-Adjusted Factors and Zombie Factor. 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 when including zombie-ness factors. The zombie-adjusted factors 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.