Government Risk Distortions

Zombies, Bailouts, and Government Suppliers *

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Abstract

Market distortions caused by intermediaries and the government lead to persistent asset pricing implications because there is a lack of diversification of intermediary and government risk. In Japan, zombie firms borrow at below-market rates. Intermediary risk prices zombies but not overall Japanese equities. Zombies differ from other bank-dependent firms because zombies rely on the government to continue allowing forbearance. This is reflected in the pricing: a government risk factor prices only zombies, and a Japanese intermediary factor prices zombies because intermediary risk covaries with government risk. Government risk exposure also determines the returns of U.S. firms with large government dependence.

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1 Introduction

Market distortions misallocate resources and lead to persistent asset pricing implications. Some market distortions stem from the actions and relationships of firms with intermediaries and the government, and cases of widespread market distortions affect firms' returns and lead to a lack of diversification in risk. I study the most straightforward and defined case of market distortions: Japanese firms that borrow at below-market rates, commonly called *zombie* firms. Banks and the government create this market distortion, and zombies' returns compensate for intermediary and government risk. When intermediaries or the government become more constrained, firms relying on banks and the government face lower returns. I show that government risk exposure also determines returns of U.S. firms with outsized government dependence.

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

I construct intermediary and government risk factors. The Japanese intermediary factor is constructed using shocks to intermediary capital and reflects the constraints of intermediaries, and I proxy for government constraints using a government risk factor constructed from sovereign credit-default swap (CDS) spreads, which reflect the market's expectation of default.

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

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

Zombie firms are not just bank-dependent firms. Zombies have greater government dependence, and this difference is reflected in asset pricing tests. I classify firms as bank-dependent using three measures: external finance dependence, bank beta, and whether the firm finances itself through long-term debt issuance. I form bank-dependent portfolios, and I show that the overall intermediary factor also prices bank-dependent portfolios, but the component of intermediary risk that is unrelated to government risk drives the result.

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

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

In the U.S., government suppliers, large banks, and auto companies rely directly on the government's budget capacity. I show that a U.S. government risk factor prices monthly portfolios of government-dependent firms and that other factors do not span the government risk factor. In each case of government dependence, government-dependent firms load more on government risk than their counterparts, and the risk exposure increases after the government announces policies that support government-dependent firms. .

I show two sets of results. First, government risk determines the expected returns of U.S. government-dependent firms. I form size-and-book-to-market portfolios from government suppliers, large banks, and auto companies separately. I show that a U.S. government risk factor prices the portfolios. Second, I conduct event studies to show that government-dependent firms have greater government risk exposure than other firms. Government suppliers rely on the government to translate taxpayer funding into purchase orders, and a budget-constrained government may cut orders. Firms with sales to the federal government are most likely to be affected by government belt-tightening, and I show that government suppliers face lower abnormal returns than non-suppliers after the 2011 U.S. sovereign debt downgrade.

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

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

Section 3 presents the Japanese intermediary asset pricing results. Section 5 concludes.

Related Literature

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

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

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

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

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

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

2 Data

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

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

Japanese Data I use Japanese market data and accounting data from Datastream and Worldscope. The data cover 1979 to 2018 and consist of the universe of Japanese stocks in Datastream and Worldscope. I restrict my sample to companies with a book value in the previous six months and at least 12 months of return history, and I exclude financials (including REITs) and stocks that have a share price less than $1 at the start of each month. I follow Asness et al. (2013) and restrict the data to a sample of liquid stocks. Each month, I sort stocks by market capitalization in descending order. Starting with the largest market capitalization stock, I include all stocks until the cumulative market capitalization is 90% of the total market capitalization for that month.

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

$$R^\star_{i,t} = r^s_{t-1} S_{i,t-1} + \left(\frac{1}{5} \sum_{j=1}^{5} r^\ell_{t-j} \right) L_{i,t-1} \tag{1}$$

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

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

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:

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

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

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

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

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

$$SovereignCDS_t = \rho_0 + \rho_1 SovereignCDS_{t-1} + u_t. \tag{3}$$

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

$$GovFac_t = -1 \times \frac{u_t}{SovereignCDS_{t-1}}, \tag{4}$$

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

The CDS data are from Markit and begin in 2002, with U.S. sovereign CDS data are available starting in 2003. Since the too big to fail event occurred in 1984, I form a synthetic U.S. sovereign CDS spread using the par-equivalent CDS spread approach, an industry standard and described in Beinstein and Scott (2006). See Appendix A for details. I use innovations to the synthetic U.S. sovereign CDS spread and Equations 3 and 4 to create the synthetic U.S. government risk factor, $GovFac_{synthetic}$.

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

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

3 Intermediated Government Dependence

I now move from examining cases of *direct* government dependence to *intermediated* government dependence. I study Japan, given the existing work that documents the country's unique zombie history—in this context, Japan is the extreme example, but I expect similar effects anywhere the government condones zombies. Figure 1 shows widespread zombies in Japan: in recent years, nearly half of my sample is considered a zombie.[‡]

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

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

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

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

Figure 2 summarizes the asset pricing results for zombie and bank-dependent portfolios. The intermediary factor prices both, but for distinct reasons. Zombies rely on the government through the intermediary sector; the government risk component of intermediary risk prices zombie portfolios because zombies' expected returns reflect the riskiness of whether assets will pay off in bad states as determined by the tightness of the government's constraints. Bank-dependent firms are not differentially affected by the government's capacity, and they face intermediary risk unrelated to government risk.

3.1 Cross-Sectional Regressions

I split my sample of Japanese companies into two buckets, zombies and non-zombies. For each bucket, I construct 25 size-and-book-to-market portfolios. The portfolios are quarterly to match the intermediary factor's frequency and are value-weighted. I form portfolios using 98% of the market capitalization (rather than 90%). Using 90% of the market capitalization gives similar price of risk results, but the number of observations is occasionally considerably lower. I use the two-step procedure in Equations 6 and 7 and the intermediary factor, $\mathbf{f} = LevFac_{JP}$, to calculate the intermediary factor's price of risk.

Table 1 shows the price of risk from cross-sectional regressions using a single factor model. The intermediary leverage factor, $LevFac_{JP}$, explains the cross-section variation of zombie portfolios but does not price non-zombies or Fama–French portfolios. The results are robust to using the capital ratio factor instead of the leverage ratio factor, adding a market factor, and including the ten momentum portfolios. Unlike the U.S., the Japanese leverage and capital factors are negatively correlated, and they have opposite price of risk signs. I discuss the signs in detail in Appendix B.

I use the intermediary leverage factor to calculate the predicted returns for zombie and non-zombie portfolios, and I plot the realized returns against the predicted returns in Figure 3. For zombie portfolios, predicted and realized returns line up near the 45-degree line. For non-zombies, the predicted returns cluster in a small range, while realized returns spread over a broader range, reflecting the failure of the intermediary factor to price non-zombie portfolios.

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

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

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

$$LevFac_{JP,t} = \underbrace{\alpha + \beta\, GovFac_{JP,t}}_{LevFac_{predicted,t}} + \underbrace{\varepsilon_t}_{LevFac_{residual,t}} \tag{5}$$

$LevFac_{predicted}$ is the predicted dependent variable. $LevFac_{residual}$ is the regression residual. I use the two components of $LevFac_{JP}$ to price portfolios following the two-step procedure in Equations 6 and 7 and $\mathbf{f} = LevFac_{predicted}$ and $\mathbf{f} = LevFac_{residual}$, separately, to calculate the prices of risk.

Table 1 shows that $LevFac_{predicted}$ prices zombie portfolios and drives the intermediary asset pricing of zombie portfolios. The orthogonal component, $LevFac_{residual}$, does not explain the cross-sectional variation of zombie returns; and in a horse-race of the two components, the predicted components have larger t-statistics. Zombie portfolios are differentially exposed to the risk that the government will no longer support forbearance, and government risk underlies the intermediary risk pricing of zombies. Non-zombies do not rely on the government's budget capacity in the same way and are not priced by the intermediary factor or either component of intermediary risk. The results are robust to using the capital ratio factor instead of the leverage factor to separate the two components, adding a market factor, and including the ten momentum portfolios.[§]

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

I identify bank-dependent firms using three measures: external-finance dependence, bank beta, and long-term debt issuance. First, I construct a measure for external-finance dependence in the spirit of Rajan and Zingales (1998), which represents the amount of a firm's desired investment that it cannot finance through internal cash flows alone. I use Datastream/Worldscope data on capex and cash flows from operations to construct firms' external-finance dependence, which is the ratio of capital expenditures less cash flows from operations to capex. To calculate the time-series of external-finance dependence for each firm, I calculate the external-finance ratio using data as available in the previous ten years. Second, I measure bank betas using each firm's bank beta using 24 to 60 months of monthly returns, as available, in the five years before July of year t, like the Fama–French pre-ranking betas. Third, Kashyap et al. (1994) define bank-dependent firms as companies without a long-term issuer rating from S&P since these firms do not have easy access to capital markets. I use an indicator for whether the firm has a long-term credit rating from Japan Credit Rating Agency, Ltd. This measure is an ex-post indicator for firms with credit ratings.

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

[§]See Table A.1, Table A.2, and Table A.3.

the zombie indicator ranging from 9% to 12%, and zombies are more bank dependent than non-zombies using each measure.

I form quarterly portfolios of bank-dependent firms, separately for each measure of bank dependence, and I price the portfolios using the intermediary factor and its components. I use the two components of $LevFac_{JP}$ to price portfolios following the two-step procedure in Equations 6 and 7 and $\mathbf{f} = LevFac_{predicted}$ and $\mathbf{f} = LevFac_{residual}$, separately, to calculate the prices of risk.

Table 2 and Figure 4 show the cross-sectional pricing results. Bank-dependent portfolios are priced by the intermediary factor and the intermediary component orthogonal to government risk, $LevFac_{residual}$. Bank-dependent portfolios are not priced by the component correlated with government risk, $LevFac_{predicted}$. The results are similar using the capital ratio factor in place of the leverage factor and adding a market factor.[¶] The intermediary factors price zombie portfolios and bank-dependent portfolios but do not price Japanese Fama–French portfolios since they do not sort in a way that gives heterogeneous exposure to intermediary beta. Sorting on bank dependence first gives portfolios an economically meaningful spread in intermediary beta.

3.2 Japanese Event Studies

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

Table 3 shows the regression of daily returns on the government risk factor in Japan. Like the U.S. result, government-dependent firms have a higher beta to government risk.

[¶]See Table A.4, Table A.5, and Table A.6.

Zombies have a 30% larger beta than non-zombies. Unlike the U.S. government-dependent firms, zombies' government dependence is indirect. Zombies exist because banks forbear on their non-performing loans, and they rely on the government to continue allowing banks to do so. Consistent with the indirect mechanism, zombies have a higher beta to government risk than non-zombies, but the effect disappears when I control for bank returns.

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

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

Figure 5 shows the cumulative abnormal returns for zombie and non-zombie firms over November 1997, using an analogous method in Equation 10. I estimate each stock's market beta using daily data up to November 2, 1997, the day before Sanyo Securities failed. I use Equation 11 to calculate each stock's abnormal return and cumulative abnormal return starting from November 3, 1997. I sort firms into five equal groups using the interest-rate gap, and I calculate the value-weighted cumulative abnormal return for the zombie and non-zombie groups. After each of the four events, the zombies earned lower cumulative abnormal returns than non-zombies.

The result is similar when sorting firms based on industry, a related but distinct measure of zombie-ness. Caballero et al. (2008) find that the manufacturing industry has a lower incidence of zombies compared to construction, real estate, wholesale and retail, and services industries, likely because the manufacturing industry faces more global competition than other industries. Thus, a firm's industry is a measure of zombie-ness separate from the balance sheet data used to calculate the interest-rate gap.

Figure 5 compares the cumulative abnormal return of manufacturing firms and companies that are not manufacturing. Datastream does not classify firms into similar industry groups so I hand-classify the manufacturing and non-manufacturing groups. The left panel shows value-weighted cumulative abnormal returns for two groups: manufacturing companies and companies in the construction, retailer, and services industries, which leaves some firms unclassified. In the right panel, I classify the remaining firms. I match the group based on which industry descriptor best fits—for example, I place "Media Agencies" into the non-manufacturing group. Both methods show that non-manufacturing firms saw large negative cumulative abnormal returns over November 1997; meanwhile, manufacturing firms' returns align with market returns.

4 Direct Government Dependence

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

I show the relationship between government risk and firms' returns using cross-sectional asset pricing tests, event studies, and international evidence.

4.1 U.S. Cross-Sectional Regressions

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

I show that the U.S. government risk factor, *GovFac*, explains the cross-section of expected returns for portfolios of U.S. government-dependent firms. I form monthly portfolios of three sets of government-dependent firms, double-sorted on size and book-to-market. First, I construct 25 portfolios of U.S. government suppliers. Government suppliers are firms with at least 10% of their annual sales to the U.S. government. Second, I form six portfolios of the largest 50 U.S. banks. Third, I form six portfolios of U.S. automakers. All portfolio returns are value-weighted. Event studies in Section 4.2 support my classifications of government-dependent firms.

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

$$R^e_{i,t} = \alpha_i + \beta'_{i,f}\mathbf{f}_t + \varepsilon_{i,t},\ i = 1, \ldots, N,\ \ t = 1, \ldots, T, \tag{6}$$

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 6:

$$\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f + \xi_i,\ i = 1, \ldots, N. \tag{7}$$

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

Table 4 shows the prices of risk from the cross-sectional regressions and GMM t-statistics. The first three columns show the price of risk estimates, pooling all the portfolios and imposing the same price of risk across them. I restrict the portfolios to those with data for 80% of the full period. In the cross-sectional regression, the government risk factor commands a positive and significant price of risk for the government-dependent portfolios. The coefficient of 0.41 means that a portfolio with $\beta_{GovFac} = 1$ carries an annualized expected return of 0.41%. Increasing the portfolio's β_{GovFac} by one standard deviation increases the annualized expected risk premium by 3.7 percentage points (PP); and the risk compensation for *GovFac* is economically large. Columns 2 and 3 show similar results with the market, size, and value factors included.

Columns 4 to 6 show that the government risk factor prices the cross-section of portfolios formed from government suppliers. The risk factor earns a positive and significant price of risk, and a one standard deviation increase in beta corresponds to a 4.8PP increase in risk premium. The GRS p-value from the time-series regressions is large, consistent with failing to reject the model. The results are robust to adding the market, size, and value factors to the model. Including these factors increases the time-series R^2 and lowers the mean average pricing error.

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

While Table 4 uses estimated betas, I can instead run two separate firm-level cross-sectional regressions using the government supplier characteristic. First, I test expected returns on an indicator of whether a company is a government supplier:

$$\mathbb{E}[R_{i,t}^e] = \gamma_0 + \gamma_1 \mathbb{I}(\text{Government Supplier}) + \xi_i. \tag{8}$$

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

$$\mathbb{E}[R^e_{i,t}] = \gamma_0 + \gamma_1(\text{Government Sales Ratio}) + \xi_i. \tag{9}$$

Table 5 shows the results from the two characteristic-based cross-sectional regressions. In the cross-section, government suppliers have higher returns than non-suppliers, and the intensity of government dependence corresponds to higher returns. The first two columns test the indicator setup and find that government suppliers' returns are 0.20pp higher on average than non-government suppliers. Since this test looks across all firms, rather than testing within suppliers, the large and significant intercept shows that non-suppliers also have positive returns. The last two columns use the intensity of the government sales ratio instead of the indicator and find a similar result. Controlling for firm size and book-to-market does not materially change the results.

Table 6 shows that other factors do not span the government risk factor, meaning the other factors do not contain *GovFac*'s economic content. The U.S. government risk factor is also not spanned on a daily or quarterly level. In the first column, I regress *GovFac* on the standard Fama–French factors and find that the government risk factor is weakly correlated with the market and *HML*, but neither is significant. Notably, *GovFac* is not spanned by any of the factors, as shown by its large and significant intercept.

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

4.2 U.S. Event Studies and International Evidence

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

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

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

4.2.1 Government Suppliers

I systematically measure a firm's government dependence by its sales to the U.S. government. I calculate each firm's annual government sales ratio as the percent of sales to the U.S. government. I consider firms with an annual government sales ratio of at least 10% to be government suppliers. I define firms with no government sales reported or a government sales ratio of less than 10% as non-suppliers. Specifically, if a company discloses no government sales, then the federal government accounts for less than 10% of that firm's sales that year. Table 7 shows examples of firms in each group. Prominent government suppliers span many industries; unsurprisingly, defense contractors like Raytheon and Northrop Grumman have high government sales ratios, but less obvious examples include Aetna, Con Edison, Corrections Corporation of America, and Walgreens. Non-suppliers span many industries as well: Amazon, Coca-Cola, Microsoft, and Walmart. In other words, sorting on government suppliers is not just a defense industry effect.

I show that government suppliers have greater government risk exposure than non-suppliers. Consistent with my prediction that government risk is a priced risk, the government sales ratio covaries with beta to the U.S. government risk factor. First, I calculate daily value-weighted portfolios for suppliers and non-suppliers and regress the portfolios' returns on the government risk factor. Table 8 column 1 shows that a portfolio that is long government suppliers and short non-suppliers significantly covaries with innovations to government risk, as predicted. Columns 2 and 3 show the long and short legs separately: while both significantly covary with government risk, the beta for government suppliers is thirty times larger than the beta for non-suppliers. The covariance of the non-suppliers portfolio with government risk isn't surprising: my definition of non-suppliers likely mixes some companies that have government sales rates just below the 10% disclosure threshold with companies that have a 0% ratio. Even if I had perfect insight into companies with no commercial relationship with the government, there are likely second-order effects—such as suppliers of suppliers—that have links to suppliers, so it's not clear the non-suppliers portfolio should have zero covariance with government risk.

Digging deeper, Figure 6 presents a scatterplot of beta to the government risk factor against the government sales ratio for each industry. The corresponding regression has a positive and significant coefficient, showing that industries with higher government sales ratios also have greater government risk exposure.

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

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

$$R_{i,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \varepsilon_{i,t}. \tag{10}$$

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

$$AR_{i,t} = R_{i,t} - \hat{R}_{i,t}. \tag{11}$$

Figure 7 plots the cumulative abnormal return for government suppliers and non-suppliers in the week after the downgrade. On August 8—the first trading session after the downgrade—government suppliers and non-suppliers both had large negative abnormal returns. But government suppliers faced a significantly larger drop, and their cumulative abnormal returns were lower over the next week, consistent with my hypothesis that government-dependent firms have greater exposure to government risk.

4.2.2 Banks

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

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

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

$$\begin{aligned} R_{i,t} = \alpha \\ &+ \beta_1 \, GovFac_{synthetic,t} \\ &+ \beta_2 \, GovFac_{synthetic,t} \times \mathbb{I}(\text{WSJ}) \\ &+ \beta_3 \, GovFac_{synthetic,t} \times \mathbb{I}(\text{Post}) \\ &+ \beta_4 \, GovFac_{synthetic,t} \times \mathbb{I}(\text{WSJ}) \times \mathbb{I}(\text{Post}) + \varepsilon_{i,t} \end{aligned} \tag{12}$$

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

Table 9 shows the regression results for commercial banks and for the top 50 commercial banks. When the government becomes constrained and $GovFac_{synthetic}$ decreases, commercial bank returns decline on average (columns 1 and 6). The coefficient of 0.007 translates to a 2PP decrease in annualized return for a one standard deviation decrease in $GovFac_{synthetic}$.

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

The result is robust to adding additional controls, using a shorter period, separate estimations for national and commercial banks, restricting the control group to only the largest 50 banks at each point in time, and restricting the sample to banks on the border of the too big to fail cutoff. The result is also insignificant in a placebo test.

Figure 8 plots the beta to the synthetic government risk factor for the 11 *WSJ* banks and the beta of the next two largest banks: Mellon Bank and Crocker National Bank. After the event, the government risk beta for the 11 *WSJ* banks jumped up. Meanwhile, the next two largest banks remained steady in their government dependence.[‖]

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

I examine Fitch's bank support ratings. Fitch Ratings' support rating assesses the likelihood that a bank receives external support—that is, government assistance—if it runs

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

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

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

To test the hypothesis, I use the members of the Bloomberg Banks Index, which includes 156 leading global bank stocks from 43 countries. Of the 156 banks, 130 have Fitch support ratings. Figure 9 shows each country's average Fitch support rating and the number of ratings included in the average. For example, all three Japanese banks in the index have an "extremely high probability of external support," consistent with Japan's long history of government support of forbearance. Banks in other developed market countries cannot rely as much on external support, and all 19 U.S. banks in the index have a support rating of 5. Emerging market countries have a higher probability of external support. China's 25 banks have an average support rating of 1.7: 12 banks have a support rating of 1, and none have a support rating over 3.

Figure 10 plots the bins of countries' support rating against bank beta to the country's government risk factor, where I calculate the government risk factors in an analogous method as for the U.S.-based *GovFac* described previously. I calculate each beta by regressing the bank's daily return against the one-day lag of the relevant country's government risk factor during the pre-crisis period. A higher beta to government risk shows greater dependence on government risk and corresponds to a higher probability of external support, and the corresponding regression shows a significant relationship.

4.2.3 Auto Companies

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

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

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

I compare the returns of the Big Three automakers against the returns of a control group of non-auto non-commercial bank firms. I exclude commercial banks from the control group because I showed their government dependence in section 4.2.2. I use the method from equation 12. Table 10 shows the result. Columns 2 and 7 show that automakers have greater government risk exposure than the control group in general: for example, the average control group firm has a government risk beta of 0.7, while the betas of the Big Three autos are almost double that at 1.3. Column 5 presents the full result. After the government support announcement, the beta to government risk increases by 1.6 for the Big Three. After the bailout announcement, when the government's constraints tighten, automakers' returns decline more than other companies. The results are robust to adding additional controls, including the market return and industry fixed effects.

Figure 11 shows the beta to the U.S. sovereign risk factor for auto companies and the control group. Before December 19, 2008, auto companies had a negative beta to the U.S. government risk factor. After the bailout announcement, the beta turned positive and increased more sharply than the control group's beta.

5 Conclusion

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

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6 Tables

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

Table 1: Intermediary Asset Pricing of Japanese Portfolios. Table presents the cross-sectional pricing results for size-and-book-to-market quarterly portfolios: 25 zombie portfolios, 25 non-zombie portfolios, and 25 Fama–French portfolios. The regressions test if the Japanese intermediary factor and its components price the portfolios. $LevFac_{JP}$ is the Japanese intermediary leverage factor, and its components are $LevFac_{predicted}$ and $LevFac_{residual}$. $LevFac_{predicted}$ is correlated with government risk, and $LevFac_{residual}$ is orthogonal to government risk. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium ($\sigma^\beta \times \lambda$) is the annualized increase in expected risk premium associated with a one standard deviation increase in the portfolio's beta to the intermediary factor or factor component. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2. See Tables A.1, A.2, and A.3 for results with the inclusion of the market factor, results using the capital ratio factor, results adding the 10 momentum portfolios, and results with a horserace between the two components of the intermediary factors.

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

Table 2: Intermediary Asset Pricing of Japanese Bank-Dependent Portfolios. Table presents the cross-sectional pricing results for quarterly portfolios: 25 size-and-book-to-market bank-dependent portfolios and 10 momentum bank-dependent portfolios. Firms are classified as bank dependent using three bank dependence measures separately, and bank-dependent portfolios are formed of bank-dependent firms. See the text for additional details on the bank dependence measures and portfolio construction. The regressions test if the Japanese intermediary factor and its components price the portfolios. $LevFac_{JP}$ is the Japanese intermediary leverage factor, and its components are $LevFac_{predicted}$ and $LevFac_{residual}$. $LevFac_{predicted}$ is correlated with government risk, and $LevFac_{residual}$ is orthogonal to government risk. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium ($\sigma^\beta \times \lambda$) is the annualized increase in expected risk premium associated with a one standard deviation increase in the portfolio's beta to the intermediary factor or factor component. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2. See Tables A.4, A.5, and A.6 for results with the inclusion of the market factor, results using the capital ratio factor, and results with a horserace between the two components of the intermediary factors.

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

Table 3: Beta of Japanese Firms to the Japanese Government Risk Factor. Table presents time-series regressions at the daily level. The dependent variable is the return in basis points. Independent variables include the Japanese government risk factor, $GovFac_{JP}$, and the Japanese value-weighted bank return. $\mathbb{I}(\text{Zombie}) = 1$ if the firm is a zombie, and 0 otherwise. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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

Table 4: Cross-Sectional Asset Pricing of U.S. Government-Dependent Portfolios. Table presents the cross-sectional pricing results for size-and-book-to-market monthly portfolios: 25 government suppliers portfolios, 6 bank portfolios, 6 auto portfolios, and 25 Fama–French portfolios. Government-dependent portfolios are required to have data for 80% of the time in the pooled regressions. The regressions test if the U.S. government-risk factor, *GovFac*, prices the portfolios. See the text for additional details on the factors and portfolios. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Ann. Risk Premium ($\sigma^\beta \times \lambda_{GovFac}$) is the annualized increase in expected risk premium associated with a one standard deviation increase in the portfolio's beta to the government risk factor. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2.

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

Table 5: Cross-Sectional Asset Pricing of U.S. Firms using Firm Characteristics. Table presents the cross-sectional pricing results for monthly firm returns. The regressions test if the government suppliers have higher expected returns, and if firms with greater government dependence have higher expected returns. Coefficients are the price of risk estimates, and Fama–MacBeth t-statistics are reported.

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

Table 6: Spanning Tests of the U.S. Government Risk Factor. Table presents time-series regressions at the monthly level. The dependent variable is the U.S. government risk factor, *GovFac*. See the text for additional details on *GovFac*. Independent variables are Fama–French factors: the excess market return, *SMB*, and *HML*. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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

Table 7: Examples of Government Suppliers and Non-suppliers. Table presents examples of government suppliers and non-suppliers. Government suppliers are firms with more than 10% of their annual sales coming from the federal government, and each company listed as a government supplier has more than a year of government sales over 10%.

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

Table 8: Beta of Government Suppliers to the U.S. Government Risk Factor. Table presents time-series regressions at the daily level. The dependent variable is the value-weighted portfolio return in percent. The government suppliers portfolio consists of firms with more than 10% of their annual sales coming from the federal government. The non-suppliers portfolio includes firms with than 10% of their annual sales coming from the federal government or no government sales reported. The independent variable is the U.S. government risk factor, *GovFac*. See the text for additional details on the *GovFac*. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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

Table 9: Beta of U.S. Commercial Banks to the Synthetic U.S. Government Risk Factor. Table presents time-series regressions run at the daily level. The dependent variable is firm i's return in percent. Independent variables are the synthetic U.S. government risk factor, $GovFac_{synthetic}$, and the factor interacted with indicator variables. See the text for additional details on $GovFac_{synthetic}$. $\mathbb{I}(\text{WSJ}) = 1$ if the bank is one of the 11 banks cited as too big to fail by *The WSJ*, and 0 otherwise. $\mathbb{I}(\text{Post}) = 1$ if the date is after September 20, 1984, and 0 otherwise. t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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

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

7 Figures

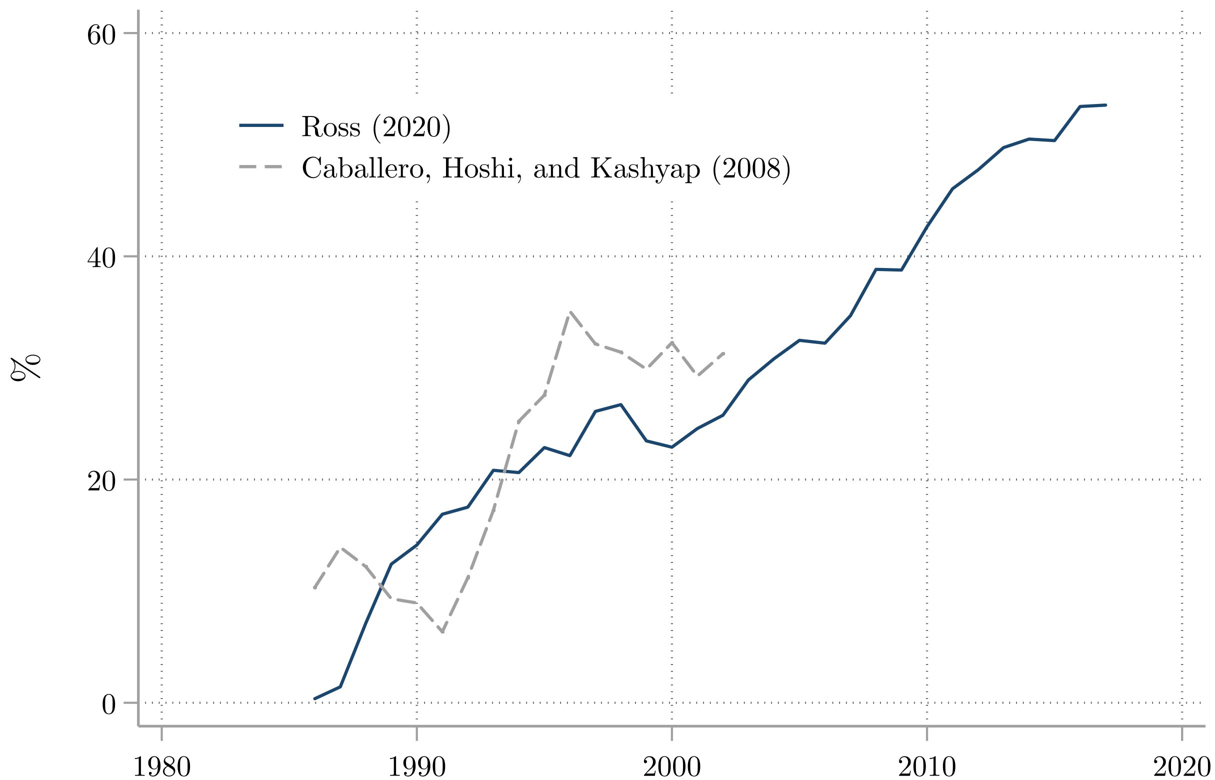

Figure 1: Percentage of Zombie Firms in Japan. Figure compares the percentage of Japanese zombies in the data and the zombie percentage from Caballero et al. (2008). Zombies are identified on a monthly basis, and the plotted percentage is the annual average.

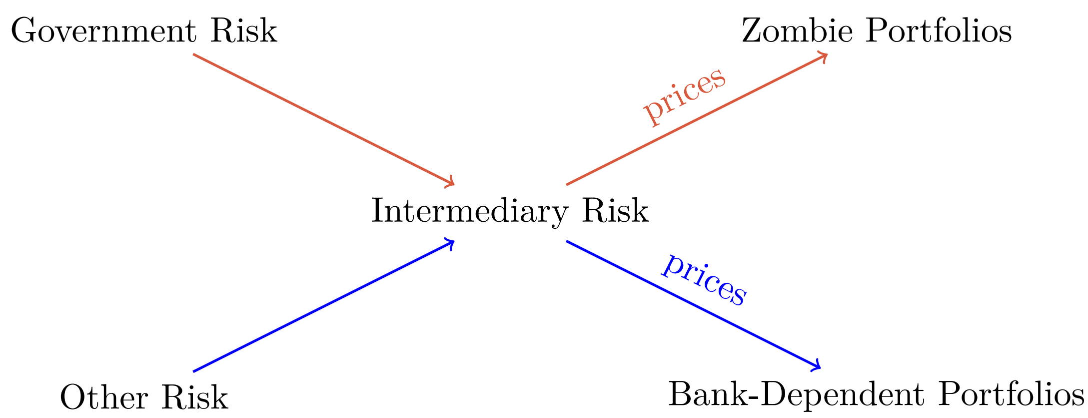

Figure 2: Intermediary Asset Pricing Summary. Figure summarizes the Japanese intermediary asset pricing results. Intermediary risk factors price zombie portfolios and bank-dependent portfolios, which differ in their government dependence. Under government-condoned forbearance, intermediary risk has two components: one correlated with government risk, one orthogonal to government risk. The former prices zombies, and the latter prices bank-dependent portfolios.

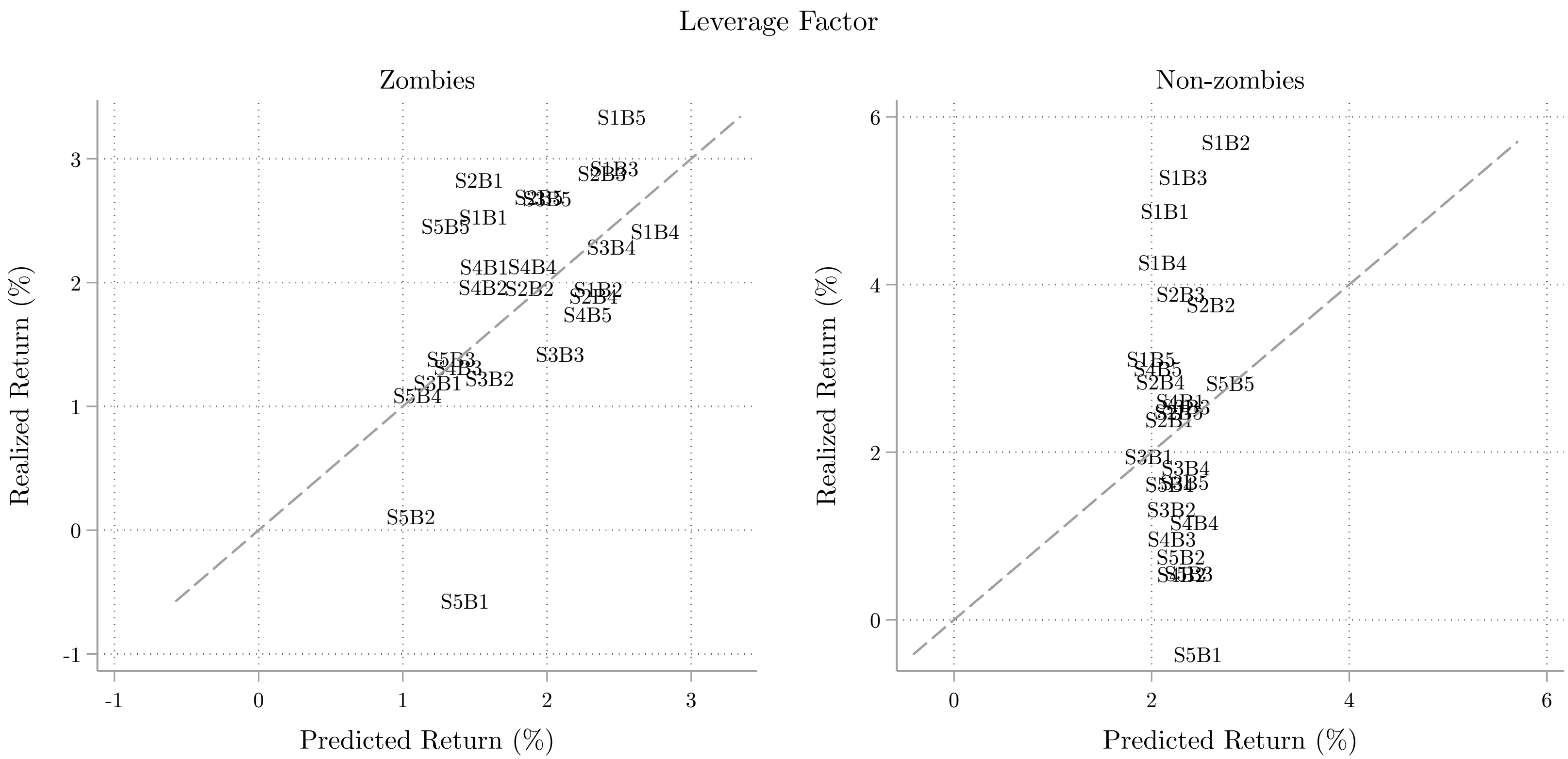

Figure 3: Realized vs. Predicted Returns using the Intermediary Leverage Factor. Figure shows the realized and predicted excess returns of size-and-book-to-market portfolios. 25 zombie portfolios and 25 non-zombie portfolios are used. Predicted returns are calculated using quarterly regressions and the intermediary leverage factor, $LevFac_{JP}$.

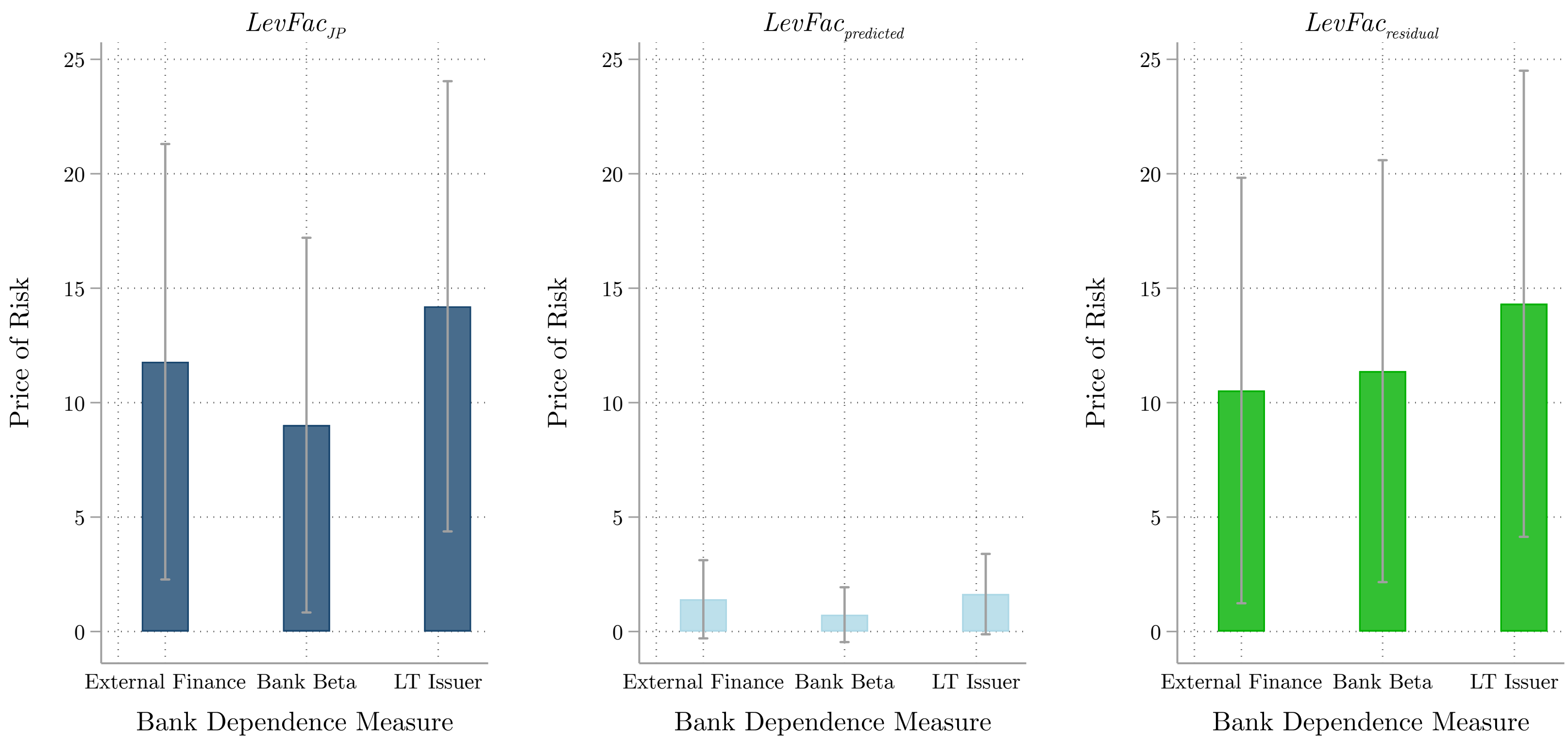

Figure 4: Price of Risk for Bank-Dependent Portfolios. Figure shows the price of risk from cross-sectional regressions of bank-dependent portfolio returns and GMM standard error bars. Each bar represents the price of risk calculated from the cross-sectional regression of 25 bank-dependent portfolios on the intermediary leverage factor or a component of the intermediary leverage factor. Three sets of 25 bank-dependent portfolios are used. Each set of portfolios is sorted on size and book-to-market, and firms are categorized as bank dependent using three separate measures of bank dependence: external finance, bank beta, and long-term issuer. $LevFac_{JP}$ is the intermediary leverage factor, and $LevFac_{predicted}$ and $LevFac_{residual}$ are its components. $LevFac_{predicted}$ is correlated with government risk, and $LevFac_{residual}$ is orthogonal to government risk. See the text for details on the construction of the factors and portfolios.

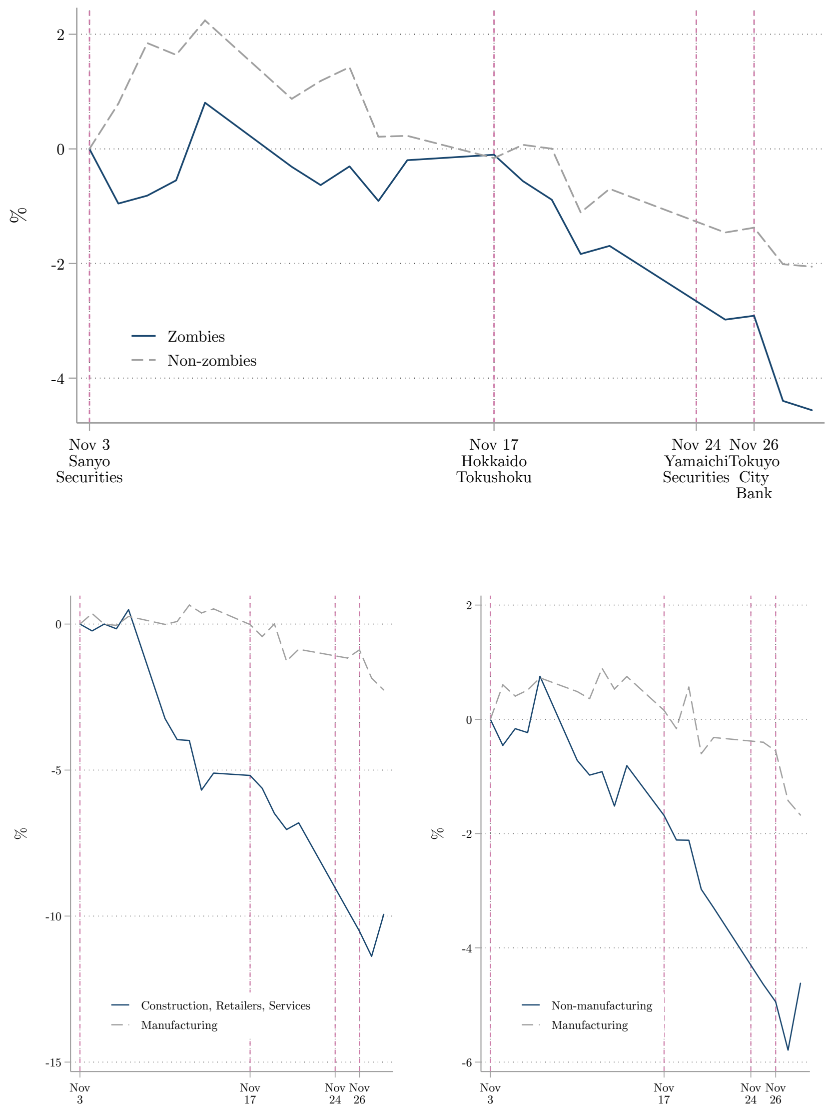

Figure 5: Cumulative Abnormal Returns in Japan, November 1997. Figure shows the daily value-weighted cumulative abnormal returns. Each firm's abnormal returns are calculated as the difference between the realized return and predicted return, which is estimated using the CAPM beta before November 3, 1997, the day of the Sanyo Securities' failure. Vertical lines mark the dates of the four bank failures. Top panel shows value-weighted cumulative abnormal returns for zombies and non-zombies. Figures in the bottom panel show the daily value-weighted cumulative abnormal returns manufacturing and non-manufacturing firms. Bottom left panel considers construction companies, retailers, and services firms as non-manufacturing. Bottom right panel includes other non-manufacturing industries. Each firm's abnormal returns are calculated as the difference between the realized return and predicted return, which is estimated using the CAPM beta before November 3, 1997, the day of the Sanyo Securities' failure. Vertical lines mark the dates of the four bank failures.

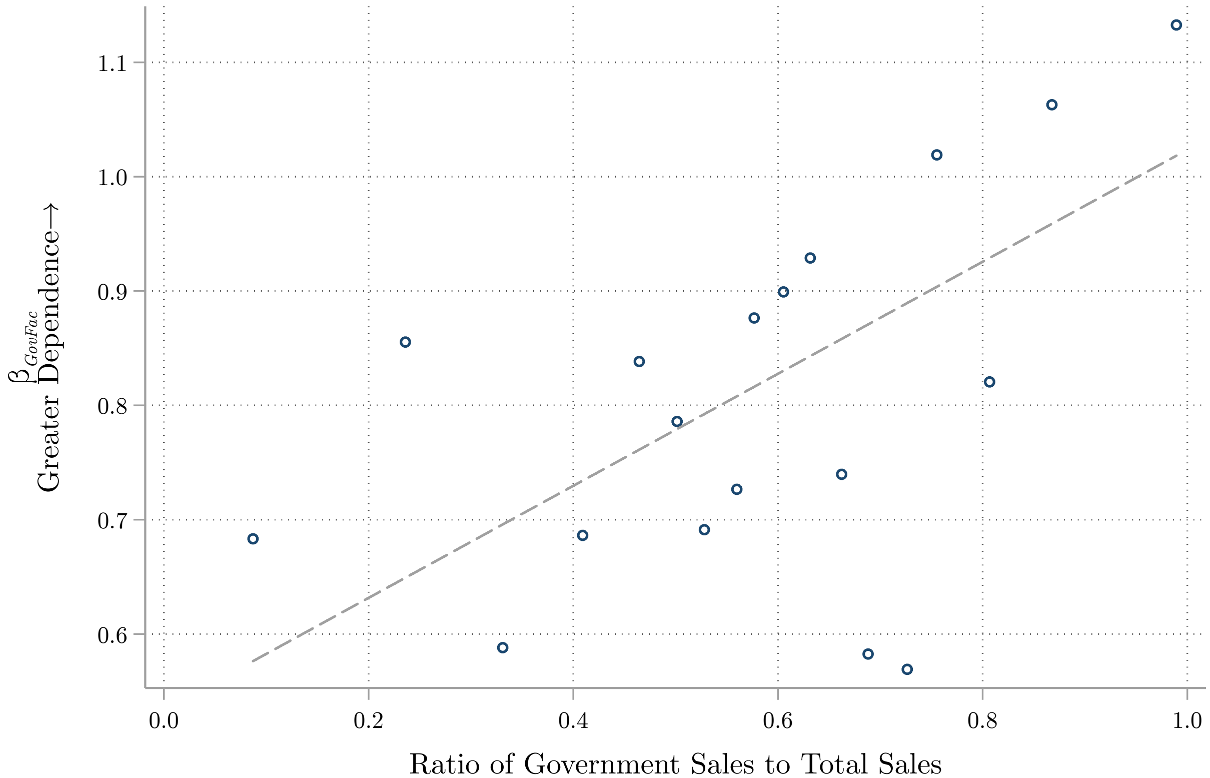

Figure 6: Government Risk and the Ratio of Government Sales To Total Sales. Figure is a binned scatterplot of beta to the U.S. government risk factor against the average government sales ratio. Each value is calculated at the industry level.

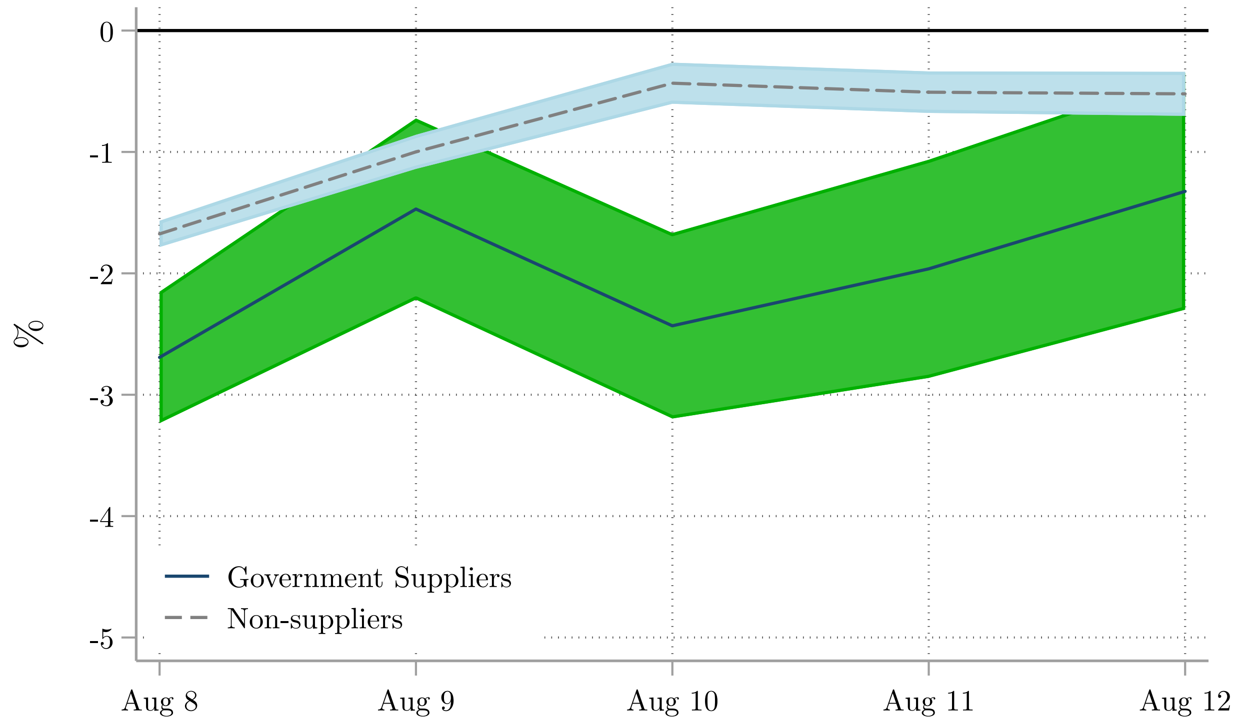

Figure 7: Cumulative Abnormal Return of Government Suppliers and Non-suppliers After the U.S. Sovereign Debt Downgrade. Figure shows the daily average cumulative abnormal returns in the week after the U.S. sovereign debt downgrade and its standard errors. I calculate each firm's abnormal returns as the difference between the realized return and predicted return using the estimated CAPM market beta before August 5, 2011, the day of the downgrade. I calculate the daily average separately for government suppliers and non-suppliers.

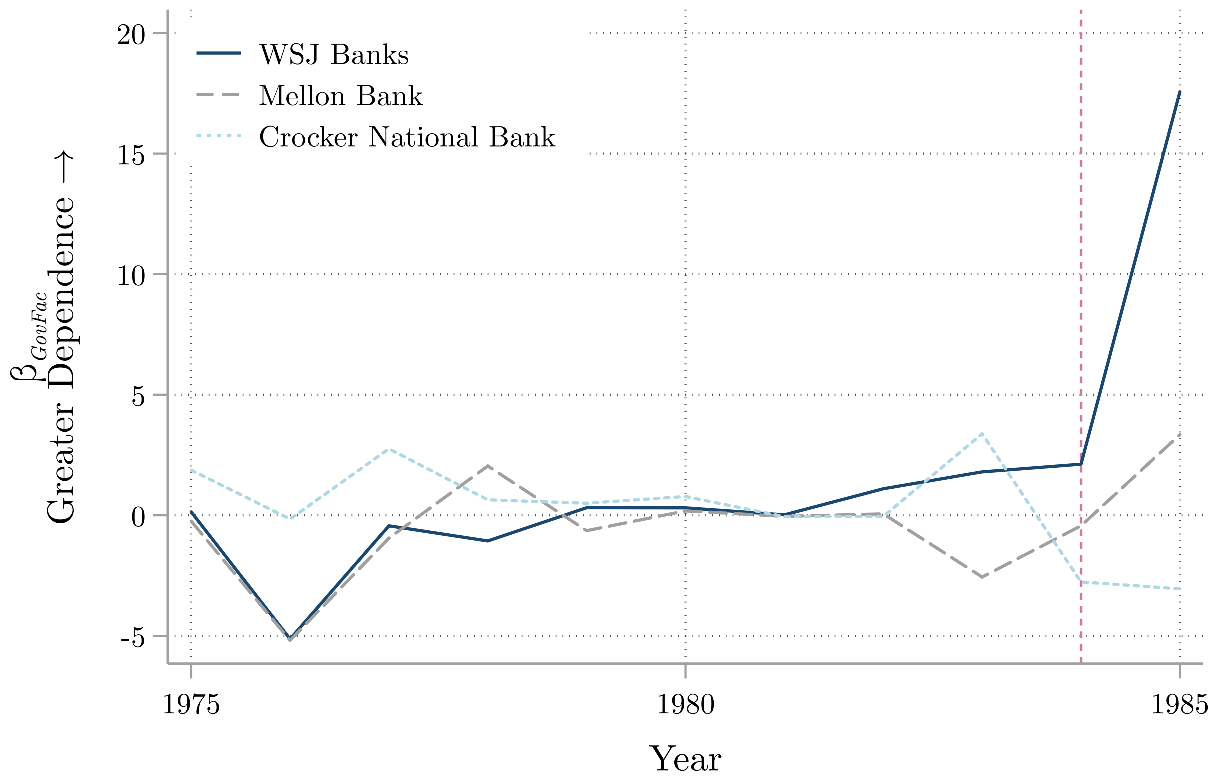

Figure 8: Beta to Synthetic U.S. Government Risk Factor. Figure shows the average beta to the synthetic U.S. government risk factor for the 11 largest banks cited by the *WSJ* and the beta for the next largest banks, Mellon Bank and Crocker National Bank. Betas are calculated monthly and averaged to the annual level. Vertical line marks 1984, the year of the too big to fail event.

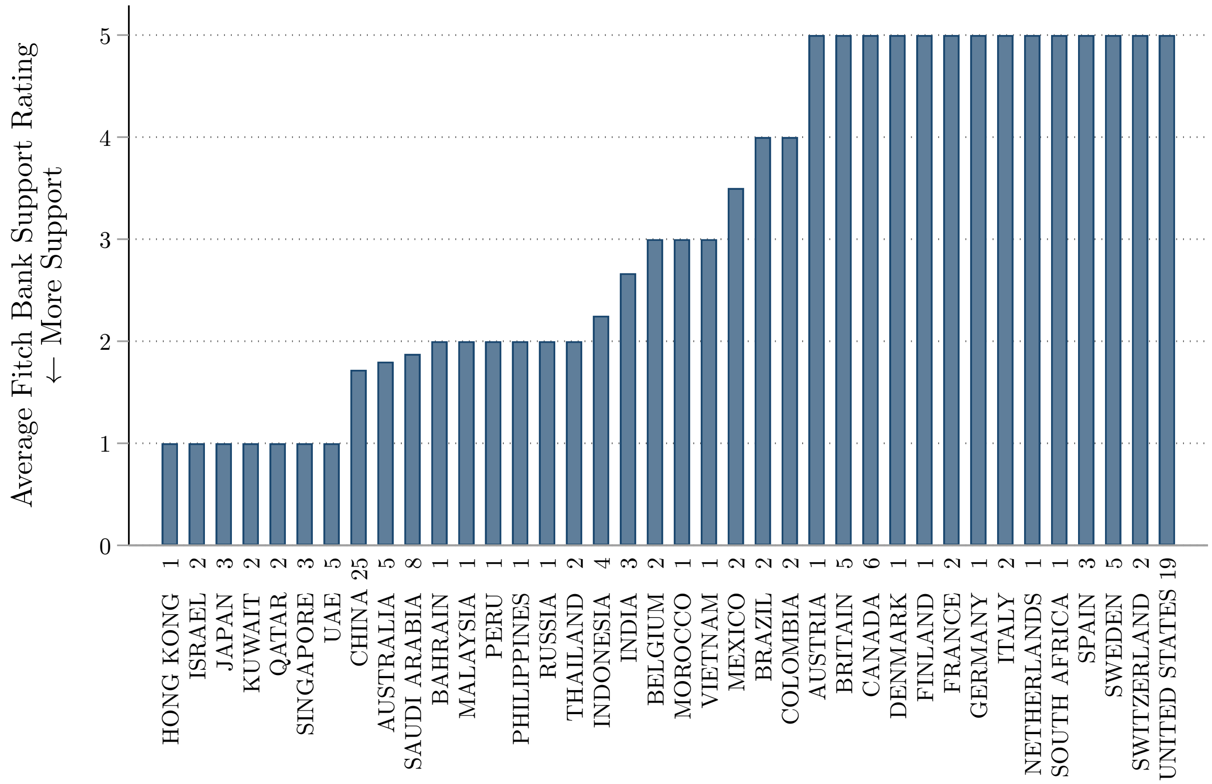

Figure 9: Average Fitch Bank Support Rating. Figure shows each country's average Fitch bank support rating, calculated as the average rating for banks included in the Bloomberg Banks Index. The number next to each country's label is the number of ratings available for that country.

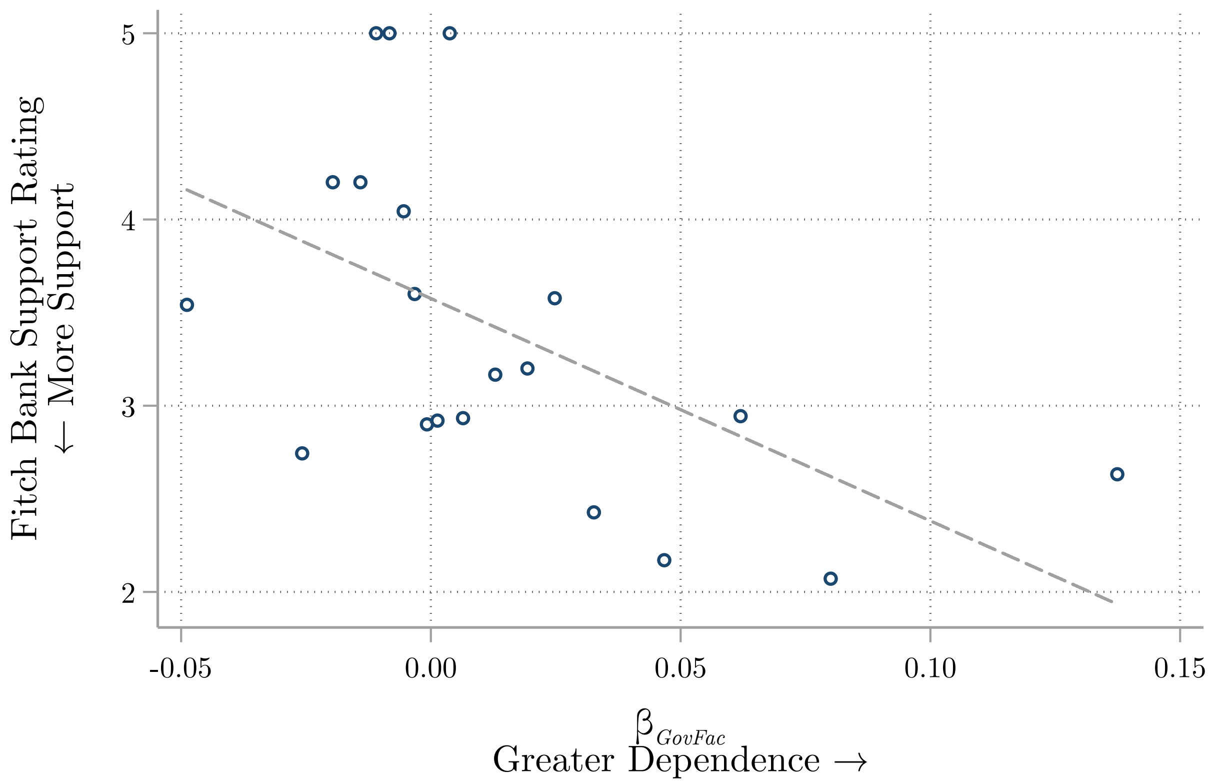

Figure 10: Fitch Bank Support Ratings and Beta to Government Risk. Figure is a binned scatterplot of countries' average Fitch bank support ratings against banks' return beta to the domestic government risk factor. I calculate a country-specific *GovFac* for each country in a method analogous to the benchmark U.S.-based *GovFac*. I exclude Saudi Arabia given its large outlier value.

Figure 11: Beta to U.S. Government Risk Factor. Figure shows the average beta to the U.S. government risk factor for the Big Three automakers and a control group of non-bank, non-autos. Betas are calculated monthly and averaged to the annual level. Vertical line marks 2008, the year of the Global Financial Crisis auto bailout.

Appendices

A Data

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

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

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

Table A.7 regresses the U.S. government risk factor on the news-implied volatility indexes and the Risk 1A portfolios. When the government becomes more constrained (*GovFac* decreases), news-implied volatility increases both in the aggregate and in the Government, Financial Intermediation, and Stock Market components. When government risk increases, firms with high Tax or Regulations risk exposure also have lower returns.

Constructing Par-equivalent CDS U.S. sovereign CDS data are from Markit and begins in 2003. For the 1984 event study, I construct a longer time-series by creating a synthetic sovereign CDS spread that is the par-equivalent CDS spread and begins in 1962. Then I use the synthetic spread and the same method from Equations 3 and 4 to form the synthetic government risk factor, $GovFac_{synthetic}$.

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

Figure A1 plots the par-equivalent synthetic sovereign CDS spread, spliced with the actual U.S.

sovereign CDS spread from Markit. The synthetic spread is demeaned and scaled to match the actual CDS spread on the first day the CDS spread data.

B Intermediary Asset Pricing Details

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

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

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

C Appendix Tables

Prices of Risk: $\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f$										
Panel A: Leverage Factor										
	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$LevFac_{JP}$	11.790	13.020	−3.212	−4.030	5.902	8.327	8.077	8.357	−3.010	−2.760
	(2.19)	(2.38)	(−0.56)	(−0.65)	(1.31)	(1.41)	(1.68)	(1.77)	(−0.59)	(−0.54)
$Mkt - R_f$		−1.576		3.741		−0.108		−1.240		2.838
		(−0.77)		(1.19)		(−0.06)		(−0.64)		(1.12)
Ann. Risk Premium ($\sigma^\beta \times \lambda$)	2.01	2.32	−0.82	−1.39	1.19	1.65	1.51	1.70	−0.75	−0.88
TS GRS p-value	0.11	0.07	0.33	0.34	0.42	0.46	0.14	0.06	0.59	0.60
MAPE (%)	2.14	0.88	2.76	1.43	2.37	0.87	1.95	0.77	2.48	1.28
TS Avg R^2	0.14	0.70	0.13	0.58	0.15	0.73	0.16	0.69	0.15	0.59
Quarters (T)	79	79	58	58	82	82	79	79	58	58
Portfolios (N)	25	25	25	25	25	25	35	35	35	35
Panel B: Capital Ratio Factor										
	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$CapFac_{JP}$	−8.675	−9.601	−2.644	−3.910	−4.585	−4.378	−6.531	−6.930	−2.728	−3.744
	(−1.97)	(−1.91)	(−0.70)	(−0.99)	(−0.91)	(−0.84)	(−1.71)	(−1.69)	(−0.72)	(−0.93)
$Mkt - R_f$		−1.531		−2.694		0.056		−1.442		−2.747
		(−0.87)		(−1.06)		(0.02)		(−0.93)		(−1.18)
Ann. Risk Premium ($\sigma^\beta \times \lambda$)	−1.97	−2.31	−1.41	−2.76	−0.93	−1.07	−1.61	−1.74	−1.39	−2.44
TS GRS p-value	0.20	0.43	0.83	0.93	0.42	0.68	0.37	0.55	0.43	0.56
MAPE (%)	2.73	0.82	2.77	1.12	2.59	0.46	2.54	0.78	2.62	0.98
TS Avg R^2	0.18	0.71	0.15	0.53	0.17	0.77	0.18	0.70	0.16	0.55
Quarters (T)	55	55	42	42	55	55	55	55	42	42
Portfolios (N)	25	25	25	25	25	25	35	35	35	35

Table A.1: Intermediary Asset Pricing of Japanese Portfolios. Table presents the cross-sectional pricing results for 25 size-and-book-to-market and 10 momentum quarterly portfolios. 35 zombie portfolios, 35 non-zombie portfolios, and 25 Fama–French portfolios are used. The regressions test if a Japanese intermediary factor prices the portfolios. $LevFac_{JP}$ is the Japanese intermediary leverage factor, and $CapFac_{JP}$ is the Japanese intermediary capital ratio factor. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium ($\sigma^\beta \times \lambda$) is the annualized increase in expected risk premium associated with a one standard deviation increase in the beta to the intermediary factor. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2.

Prices of Risk: $\mathbb{E}[R^e_{i,t}] = \lambda_0 + \hat{\beta}'_{i,f}\lambda_f$										
Panel A: *LevFac*$_{predicted}$										
	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$LevFac_{predicted}$	1.365	1.372	0.630	0.589	1.340	1.323	1.493	1.506	0.834	0.820
	(1.96)	(2.02)	(0.76)	(0.79)	(2.06)	(1.95)	(1.99)	(2.14)	(1.05)	(1.06)
$Mkt - R_f$		−0.780		0.064		−0.670		−0.823		−0.284
		(−0.46)		(0.03)		(−0.30)		(−0.47)		(−0.13)
Ann. Risk Premium	1.91	1.83	1.47	1.47	2.14	2.30	2.09	1.98	1.90	1.96
TS GRS p-value	0.23	0.33	0.11	0.12	0.35	0.53	0.50	0.62	0.58	0.65
MAPE (%)	3.05	0.74	3.26	1.37	2.77	0.57	3.03	0.68	3.22	1.15
TS Avg R^2	0.02	0.70	0.03	0.55	0.01	0.79	0.02	0.71	0.03	0.57
Quarters (T)	65	65	50	50	65	65	65	65	50	50
Portfolios (N)	25	25	25	25	25	25	35	35	35	35
Panel B: *LevFac*$_{residual}$										
	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$LevFac_{residual}$	7.781	8.909	7.920	6.879	9.320	9.906	7.068	7.692	7.278	6.924
	(1.69)	(1.78)	(1.31)	(1.24)	(1.60)	(1.50)	(1.69)	(1.79)	(1.25)	(1.32)
$Mkt - R_f$		−0.749		0.757		0.113		−0.943		0.225
		(−0.49)		(0.25)		(0.05)		(−0.60)		(0.10)
Ann. Risk Premium	1.62	1.84	1.80	2.00	1.42	1.98	1.56	1.67	1.63	1.93
TS GRS p-value	0.24	0.24	0.57	0.61	0.08	0.13	0.33	0.30	0.82	0.88
MAPE (%)	2.18	0.87	2.60	1.21	2.42	0.84	1.96	0.77	2.37	1.00
TS Avg R^2	0.18	0.71	0.12	0.55	0.18	0.79	0.19	0.71	0.13	0.57
Quarters (T)	65	65	50	50	65	65	65	65	50	50
Portfolios (N)	25	25	25	25	25	25	35	35	35	35
Panel C: *LevFac*$_{predicted}$ and *LevFac*$_{residual}$										
	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$LevFac_{predicted}$	1.070	0.914	0.401	−0.039	1.242	0.861	1.396	1.337	0.658	0.450
	(1.64)	(1.34)	(0.54)	(−0.06)	(1.76)	(1.05)	(2.10)	(1.90)	(1.01)	(0.80)
$LevFac_{residual}$	2.909	4.141	6.421	6.576	1.743	3.922	0.871	1.317	4.672	4.899
	(0.53)	(0.69)	(1.09)	(1.10)	(0.29)	(0.69)	(0.16)	(0.22)	(0.87)	(0.95)
$Mkt - R_f$		−0.629		0.624		−0.528		−0.743		−0.138
		(−0.39)		(0.23)		(−0.24)		(−0.43)		(−0.07)
TS GRS p-value	0.19	0.38	0.12	0.18	0.35	0.62	0.43	0.65	0.62	0.75
MAPE (%)	3.05	0.72	3.39	1.30	2.77	0.67	3.03	0.69	3.36	1.09
TS Avg R^2	0.20	0.72	0.15	0.57	0.19	0.81	0.22	0.72	0.16	0.59
Quarters (T)	65	65	50	50	65	65	65	65	50	50
Portfolios (N)	25	25	25	25	25	25	35	35	35	35

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

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

Panel A: *CapFac$_{predicted}$*

	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$CapFac_{predicted}$	−2.735	−2.749	−1.262	−1.180	−2.684	−2.649	−2.990	−3.018	−1.671	−1.643
	(−1.96)	(−2.02)	(−0.76)	(−0.79)	(−2.06)	(−1.95)	(−1.99)	(−2.14)	(−1.05)	(−1.06)
$Mkt - R_f$		−0.780		0.064		−0.670		−0.823		−0.284
		(−0.46)		(0.03)		(−0.30)		(−0.47)		(−0.13)
Ann. Risk Premium	−1.88	−1.81	−1.45	−1.45	−2.11	−2.26	−2.05	−1.95	−1.88	−1.93
TS GRS p-value	0.23	0.31	0.18	0.19	0.26	0.41	0.48	0.57	0.68	0.74
MAPE (%)	2.83	0.73	2.97	1.32	2.68	0.51	2.76	0.67	2.88	1.08
TS Avg R^2	0.02	0.70	0.03	0.55	0.01	0.79	0.02	0.71	0.03	0.57
Quarters (T)	65	65	50	50	65	65	65	65	50	50
Portfolios (N)	25	25	25	25	25	25	35	35	35	35

Panel B: *CapFac$_{residual}$*

	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$CapFac_{residual}$	−7.487	−9.234	−3.520	−2.616	−5.221	−11.030	−6.121	−7.455	−2.942	−2.466
	(−1.99)	(−1.85)	(−0.87)	(−0.74)	(−1.00)	(−1.11)	(−1.87)	(−1.76)	(−0.78)	(−0.74)
$Mkt - R_f$		−1.000		0.124		0.414		−0.962		−0.149
		(−0.59)		(0.05)		(0.15)		(−0.63)		(−0.07)
Ann. Risk Premium	−1.88	−2.13	−1.38	−1.47	−0.87	−1.77	−1.61	−1.68	−1.18	−1.35
TS GRS p-value	0.23	0.22	0.61	0.70	0.09	0.15	0.33	0.32	0.77	0.86
MAPE (%)	2.18	0.89	2.55	1.24	2.42	0.89	1.96	0.78	2.32	1.02
TS Avg R^2	0.15	0.70	0.13	0.55	0.15	0.78	0.15	0.71	0.14	0.57
Quarters (T)	65	65	50	50	65	65	65	65	50	50
Portfolios (N)	25	25	25	25	25	25	35	35	35	35

Panel C: *CapFac$_{predicted}$* and *CapFac$_{residual}$*

	25 Size-and-B/M Portfolios						25 Size-and-B/M + 10 Mom Portfolios			
	Zombies		Non-zombies		Fama–French		Zombies		Non-zombies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$CapFac_{predicted}$	−1.839	−1.752	−0.857	−0.615	−2.696	−2.403	−2.436	−2.330	−1.495	−1.406
	(−1.51)	(−1.38)	(−0.59)	(−0.51)	(−1.84)	(−1.54)	(−1.97)	(−1.85)	(−1.13)	(−1.10)
$CapFac_{residual}$	−5.026	−6.788	−2.139	−1.754	0.138	−1.052	−2.664	−4.110	−1.013	−0.805
	(−1.44)	(−1.49)	(−0.63)	(−0.51)	(0.02)	(−0.17)	(−0.79)	(−0.98)	(−0.29)	(−0.25)
$Mkt - R_f$		−0.643		−0.153		−0.608		−0.511		−0.403
		(−0.40)		(−0.06)		(−0.28)		(−0.32)		(−0.19)
TS GRS p-value	0.24	0.39	0.10	0.17	0.24	0.45	0.43	0.61	0.41	0.57
MAPE (%)	2.83	0.68	3.14	1.29	2.68	0.52	2.76	0.64	3.05	1.06
TS Avg R^2	0.16	0.71	0.16	0.57	0.16	0.80	0.17	0.71	0.18	0.59
Quarters (T)	65	65	50	50	65	65	65	65	50	50
Portfolios (N)	25	25	25	25	25	25	35	35	35	35

Table A.3: Intermediary Asset Pricing with Components of $CapFac_{JP}$. Table presents the cross-sectional pricing results for 25 size-and-book-to-market and 10 momentum quarterly portfolios. 35 zombie portfolios, 35 non-zombie portfolios, and 25 Fama–French portfolios are used. The regressions test if the components of $CapFac_{JP}$, the Japanese intermediary capital ratio factor, price the portfolios. $CapFac_{predicted}$ is the component correlated with government risk, and $CapFac_{residual}$ is the component orthogonal to government risk. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium is the annualized increase in expected risk premium associated with a one standard deviation increase in the beta to the intermediary factor component: $\sigma^{\beta} \times \lambda$. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2.

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

Panel A: *LevFac$_{JP}$*

Bank Dependence Measure	External Finance				Bank Beta				Long-Term Issuer			
	Bank-Dependent		Not Bank-Dep.		Bank-Dependent		Not Bank-Dep.		Bank-Dependent		Not Bank-Dep.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LevFac$_{JP}$	11.787	12.150	3.622	4.624	9.017	12.233	4.453	5.526	14.209	10.676	0.836	1.401
	(2.43)	(2.59)	(0.82)	(1.08)	(2.16)	(2.70)	(1.09)	(1.27)	(2.83)	(2.00)	(0.22)	(0.38)
$Mkt - R_f$		−2.110		0.451		2.032		−0.040		−5.218		0.160
		(−1.12)		(0.22)		(0.82)		(−0.02)		(−2.63)		(0.09)
Ann. Risk Premium	3.02	2.94	0.77	0.96	2.32	2.86	0.89	1.03	3.08	1.93	0.26	0.34
TS GRS p-value	0.16	0.18	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01
MAPE (%)	1.96	1.00	2.33	1.24	2.34	1.25	2.35	1.13	2.13	1.27	2.24	1.34
TS Avg R^2	0.20	0.65	0.12	0.62	0.19	0.63	0.09	0.59	0.11	0.68	0.15	0.60
Quarters (T)	68	68	73	73	79	79	75	75	75	75	79	79
Portfolios (N)	35	35	35	35	35	35	35	35	35	35	35	35

Panel B: *CapFac$_{JP}$*

Bank Dependence Measure	External Finance				Bank Beta				Long-Term Issuer			
	Bank-Dependent		Not Bank-Dep.		Bank-Dependent		Not Bank-Dep.		Bank-Dependent		Not Bank-Dep.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CapFac$_{JP}$	−7.459	−7.523	−12.769	−12.776	−9.645	−9.797	−9.204	−9.143	−10.011	−9.178	−7.955	−7.502
	(−1.44)	(−1.40)	(−2.06)	(−2.08)	(−1.96)	(−1.91)	(−1.58)	(−1.60)	(−2.31)	(−2.16)	(−1.71)	(−1.52)
$Mkt - R_f$		−1.941		−3.734		−1.834		−2.445		−4.153		−2.876
		(−0.84)		(−2.11)		(−0.82)		(−1.24)		(−1.83)		(−2.03)
Ann. Risk Premium	−2.54	−2.56	−3.53	−4.07	−3.50	−3.71	−2.62	−3.19	−3.87	−3.38	−2.80	−2.46
TS GRS p-value	0.32	0.53	0.02	0.04	0.15	0.20	0.05	0.08	0.08	0.15	0.34	0.55
MAPE (%)	2.37	0.88	2.55	0.97	2.73	0.91	2.33	0.93	2.37	1.10	2.45	1.03
TS Avg R^2	0.23	0.66	0.12	0.62	0.24	0.66	0.11	0.57	0.14	0.63	0.16	0.60
Quarters (T)	55	55	53	53	55	55	55	55	53	53	55	55
Portfolios (N)	35	35	35	35	35	35	35	35	35	35	35	35

Table A.4: Intermediary Asset Pricing of Bank-Dependent Portfolios. Table presents the cross-sectional pricing results for quarterly portfolios: 25 size-and-book-to-market bank-dependent portfolios and 10 momentum bank-dependent portfolios. Firms are classified as bank dependent using three bank dependence measures separately, and bank-dependent portfolios are formed of bank-dependent firms. See the text for additional details on the bank dependence measures and portfolio construction. Not bank-dependent portfolios are formed using the other firms. See the text for additional details on the bank dependence measures and portfolio construction. The regressions test if a Japanese intermediary factor prices the portfolios. *LevFac$_{JP}$* is the Japanese intermediary leverage factor, and *CapFac$_{JP}$* is the Japanese intermediary capital ratio factor. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium is the annualized increase in expected risk premium associated with a one standard deviation increase in the beta to the intermediary factor: $\sigma^{\beta} \times \lambda$. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2.

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

Table A.5: Intermediary Asset Pricing of Bank-Dependent Portfolios with Components of *LevFac*$_{JP}$. Table presents the cross-sectional pricing results for quarterly portfolios: 25 size-and-book-to-market bank-dependent portfolios and 10 momentum bank-dependent portfolios. Firms are classified as bank dependent using three bank dependence measures separately, and bank-dependent portfolios are formed of bank-dependent firms. See the text for additional details on the bank dependence measures and portfolio construction. The regressions test if the components of *LevFac*$_{JP}$, the Japanese intermediary leverage factor, price the portfolios. *LevFac*$_{predicted}$ is the component correlated with government risk, and *LevFac*$_{residual}$ is the component orthogonal to government risk. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium is the annualized increase in expected risk premium associated with a one standard deviation increase in the beta to the intermediary factor component: $\sigma^{\beta} \times \lambda$. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2.

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

Table A.6: Intermediary Asset Pricing of Bank-Dependent Portfolios with Components of $CapFac_{JP}$. Table presents the cross-sectional pricing results for quarterly portfolios: 25 size-and-book-to-market bank-dependent portfolios and 10 momentum bank-dependent portfolios. Firms are classified as bank dependent using three bank dependence measures separately, and bank-dependent portfolios are formed of bank-dependent firms. See the text for additional details on the bank dependence measures and portfolio construction. The regressions test if the components of $CapFac_{JP}$, the Japanese intermediary capital ratio factor, price the portfolios. $CapFac_{predicted}$ is the component correlated with government risk, and $CapFac_{residual}$ is the component orthogonal to government risk. See the text for additional details on the factors. Coefficients are the price of risk estimates, and GMM t-statistics are reported. Intercept is included in each regression but omitted from the table. Ann. Risk Premium is the annualized increase in expected risk premium associated with a one standard deviation increase in the beta to the intermediary factor component: $\sigma^{\beta} \times \lambda$. TS GRS p-value is the p-value of the Gibbons–Ross–Shanken test of whether the pricing errors are jointly zero. MAPE is the mean absolute pricing error. TS Avg R^2 is the average time-series R^2.

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

Table A.7: Correlation of the U.S. Government Risk Factor with Other Government Risk Measures. Table presents time-series regressions at the monthly level. The dependent variable is the government risk factor. The independent variables are other government risk measures, including news-implied volatility indexes from Manela and Moreira (2017) and Risk 1A long-short portfolio returns from Ross (2019). t-statistics using robust standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

D Appendix Figures

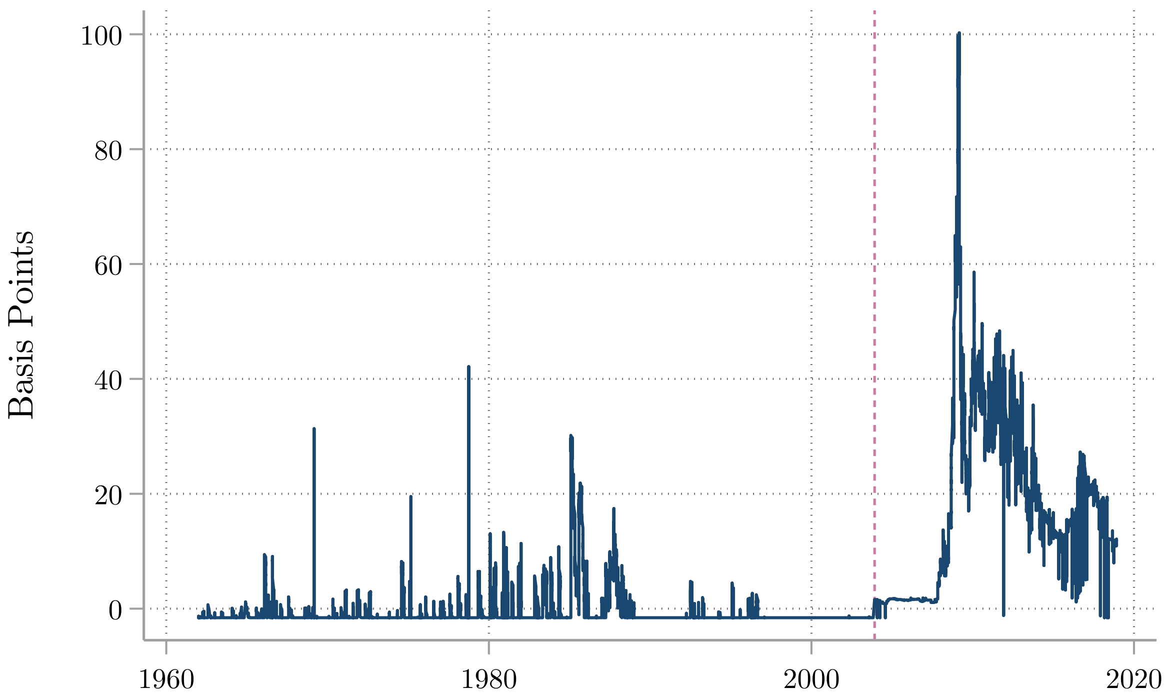

Figure A1: Synthetic U.S. Sovereign CDS Spread. Figure shows the par-equivalent CDS spread, demeaned and scaled, and spliced with the U.S. sovereign CDS spread. See Appendix A for details on the construction.