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ABSTRACT

In most countries, equity is a cheap source of funding for a country's largest financial institutions. On average, the stocks of the top 10% financial companies in a country account for over a quarter of total market capitalization, but these stocks earn returns that are significantly lower than stocks of non-financial firms of the same size and with the same risk exposures. In a bailout-augmented asset pricing model with rare disasters, country characteristics that inform the likelihood of a bailout should predict stock returns. We find greater financial pricing anomalies for the largest banks in developed countries with a highly concentrated and large banking sector and fiscally strong governments, but smaller anomalies in countries with strong corporate governance, government integrity, and property rights as well as high bankruptcy costs. The pricing discrepancy widens in anticipation of large stock market and GDP declines, as the bailout-augmented asset pricing model would predict.

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A data appendix is available at http://www.nber.org/data-appendix/w22355

1 Introduction

There is a wealth of evidence from credit markets that implicit government guarantees reduce the borrowing costs of large financial institutions. Our research shows that the largest financial institutions (the top 10%) seem to benefit from a lower cost of equity capital, but the size of the effect depends on a country's institutional and macroeconomic characteristics.

Government guarantees extended to financial institutions absorb risk that is otherwise borne by their creditors and shareholders. These guarantees not only reduce the risk that financial stocks are exposed to, but also impact the equilibrium stock returns after netting out the adjustment for standard risk. In the Kelly, Lustig, and Van Nieuwerburgh (2016) bailout-augmented dynamic asset pricing model, which builds on the rare event models of Backus, Chernov, and Martin (2011); Gabaix (2012); Wachter (2013), financial stocks that benefit from guarantees earn low risk-adjusted returns during normal times, in anticipation of shareholder bailouts in event of disasters. Under assumption of bailout, all firm and country characteristics that determine the likelihood and extent of bailouts also predict risk-adjusted returns on financial stocks. We find empirical evidence in a large panel of countries that supports these predictions of the model.

The clear implication is that regulators should not use stock-based risk measures, because these inevitably reflect the value of the guarantee. For example, Atkeson, Eisfeldt, and Weill (2013) find no difference in financial soundness between U.S. financial and non-financial institutions prior to the 2007-2008 crisis, while Sarin and Summers (2016) find that investors do not see large U.S. banks as less risky after the new wave of regulations and financial reforms. The authors attribute this to a decline in the franchise value of banks, but our results indicate that the repricing of government guarantees may also be the reason (see Bond and Goldstein (2015) for a theoretical analysis of the pitfalls of government intervention when the government relies on market prices).

This paper makes three contributions. Our first contribution is to establish that equity is a cheap source of capital for the very largest banks. One can see in Figure 1 that financial institutions that exceed the 90th size percentile in their home country earn negative risk-adjusted returns that are statistically and economically significant. This is truly a size effect rather than a market capitalization effect (Berk (1997) discusses the distinction). The largest financial firms, measured by market cap (book value), earn 3.41% (5.97%) lower returns than the largest non-financial firms after netting out risk compensation. Consistent with the Minton, Stulz, and Taboada (2017) findings for the U.S., we do not find similar effects for medium-sized banks.[1] We also uncover significant differences between developed and emerging markets. In developed markets, only the largest banks in the top size decile deliver negative risk-adjusted returns (-3.29% per year); other financials do not. This is an important anomaly. On average, the largest financial stocks account for 27% of the total market capitalization in our sample of countries. Thus, we see that over the entire sample, the implied subsidy to the cost of equity capital for large financial firms is 2.68% of gross domestic product (GDP). Furthermore, unlike other anomalies (for e.g., the momentum anomaly), this anomaly does not rely on sophisticated dynamic trading strategies, but instead is highly persistent at the firm level, and presumably has large effects on equilibrium allocations as a result (Van Binsbergen and Opp (2017)).[2]

Our second contribution is that banks' cost of equity adjusts in anticipation of a financial crisis. Bank stock investors partly anticipate financial crises, contrary to the credit spread evidence reported by Krishnamurthy, Muir, and Yale (2015) and the stock market evidence in Muir (2016) and Baron and Xiong (2017).[3] In that stock markets price in guarantees that are activated in financial crises, we find that an increase in the expected return gap between small and large banks, measured by the difference in dividend yields, forecasts large drops in GDP and the stock market. This is a discount rate effect. In a rare disaster model with time-varying probabilities (Gabaix (2012); Wachter (2013)), an increased probability of disaster increases the disaster risk premium spread between small and large banks, provided that large banks are perceived to benefit from a stronger government guarantee.

Finally, equity is a cheaper source of funding for large banks when bailouts seem more likely and more valuable. We correlate the spread in the average risk-adjusted return on size-sorted portfolios of financial firms for each country with the regulatory, policy, and institutional framework of the each country. Assuming efficient markets and no implicit bailouts, these correlations should be insignificant. Nor are these cross-sectional effects consistent with mispricing or behavioral biases. Rather they point to a rational pricing of government guarantees by bank shareholders, consistent with the bailout-augmented asset pricing model. In a placebo test, we did not find similar correlations for non-financials.

[1] Minton, Stulz, and Taboada (2017) define large banks as banks with total assets in excess of $50 bn.

[2] Exposure to this anomaly also requires very limited turnover, which implies that adjusting for transaction costs would have a very limited effect on its size. Except during financial crises, there is no evidence to suggest that shorting large financial firms is costlier than shorting large non-financial firms.

[3] It is rational to expect large banks to fare better during crises. We also verify that large financial firms fare much better during economic crises in developed countries, even though they are more levered than smaller banks. A portfolio that goes long in large financial firm stocks and shorts small financial firm stocks on average gains 16% during an economic crisis. Finally, we find find that on average nearly 1% of the firms in the bottom 10th decile are delisted during an given quarter that a country spends in an economic or financial crisis, while the corresponding number for the top 10th decile is only 0.20%.

We identify three main determinants of our results the characteristics of (i) the banking industry itself, (ii) the government, and (iii) the institutional environment. First, the risk-adjusted large-minus-small return spread is wider in countries with a large depositor base, a dense network of branches, and a heavily concentrated banking sector; all of these raise the likelihood of a bailout. Second, the size of the risk-adjusted large-minus-small return spread also increases with the fiscal health of the government and the size of its central bank balance sheet. Implicit bailout guarantees are credible only if governments have the resources to back up these promises.[4] Third, institutions matter as well. The large-minus-small spread is significantly wider than average in countries with a common law legal system, and lower than average in countries with a Scandinavian legal system as well in countries with high perceived government integrity and stronger property rights. La Porta, Lopez-de Silanes, Shleifer, and Vishny (2000), for example, show that shareholders are perceived to be better protected from expropriation in common law countries. Governments in common law countries may be legally unable or else reluctant to wipe out the shareholders of large financial institutions in the process of a bailout.[5]

Spreads are also wider in countries with weaker corporate disclosure and governance, as well as weaker business regulations. Better corporate governance may reduce risk-taking in large banks, possibly by limiting executive compensation thus reducing the value of the guarantee (Acharya, Amihud, and Litov (2011) and Bebchuk, Cohen, and Spamann (2010)). Spreads are negatively correlated with bankruptcy costs, presumably because the banks are less likely to increase leverage when the cost of bankruptcy is high. While there are other possible explanations for our findings, such as missing risk factors or behavioral issues, these would have trouble accounting for these cross-sectional correlations.

Large financial institutions do have high betas and higher systematic volatility. Yet, our findings are not another example of the low-risk anomaly that has been documented for non-financials (see, e.g., Ang, Hodrick, Xing, and Zhang (2009); Baker, Bradley, and Wurgler (2011)). We find no evidence to support a betting-against-beta explanation as in Frazzini and Pedersen (2014). Large financial firms earn low returns even when compared with large non-financial firms with the same betas and idiosyncratic volatility. In addition, the returns on the largest financial firms do not co-vary with the Frazzini and Pedersen (2014)

[4] Acharya, Drechsler, and Schnabl (2014) find that European bank credit default swap (CDS) spreads were highly correlated with sovereign risk of the country of origin during the 2008 crisis. Our results indicate that sovereign risk is always a large determinant of bank stock valuations, even before crises.

[5] There are some recent judgements that support this notion. Recently, the U.S. courts ruled that the Federal Reserve had illegally taken a large equity stake in AIG in 2008, thus expropriating its shareholders (New York Times, June 15, 2015), while Fannie and Freddie shareholders have also challenged the Treasury's profit sweep in courts. We also find that this common law effect is mitigated by stronger corporate governance or creditor rights.

betting-against-beta factors.

Baron and Xiong (2017) find that U.S. bank dividend yields do not forecast bank crashes, while credit expansion does, which they interpret as evidence that bank shareholders neglect tail risk and are at times overly optimistic, possibly because of extrapolation (Gennaioli, Shleifer, and Vishny (2012) Barberis, Shleifer, and Vishny (1998); Barberis, Greenwood, Jin, and Shleifer (2015)). Our work suggests that bank shareholders price tail risk differentially into large and small bank stock prices, because an increase in the spread in bank dividend yields forecasts stock market and GDP crashes. We cannot rule out that bank shareholders are overly optimistic at times, but their optimism seems limited to the largest banks, and concentrated in countries with regimes that favor shareholders of those banks.

If markets are efficient, then bank equity is not an expensive source of funding, as explained by Admati, DeMarzo, Hellwig, and Pfleiderer (2011), and imposing higher capital requirements does not destroy bank value. Baker and Wurgler (2015) counter that there is a low-risk anomaly in U.S. financials, and that increased capital requirements may reduce the overall value of banks, because the reduction in volatility and leverage increases the equity cost of capital. Our international evidence does not support the idea that leverage-constrained investors (or any other investors) are responsible for bidding up the prices of large bank stocks. Instead, we find evidence that equity is always a cheap source of funding for the largest banks in a country. There is no obvious behavioral explanation for our findings.

There is a large literature on size effects in stock returns (see Banz (1981), Basu (1983), Fama and French (1993), Lakonishok, Shleifer, and Vishny (1994), Berk (1997) among others). Most of these papers exclude financial stocks, presumably because of their high leverage. More recently, Gandhi and Lustig (2015) (GL hereafter) analyze the size effect in bank stock returns in the U.S. and show that the largest commercial banks in the U.S. have significantly lower risk-adjusted returns than small banks.[6]

Our work is also related to other research that shows direct evidence from options markets that tail risk in the financial sector is priced differently.[7] Kelly, Lustig, and Van Nieuwerburgh (2016) find that out-of-the-money index put options of bank stocks were relatively cheap during the recent financial crisis

[6]They find a considerable anomaly for U.S. bank stock returns. The average risk-adjusted return on the last decile portfolio of bank stocks with the highest market capitalization (or book value) exceeds the average risk-adjusted return on the first decile portfolio of bank stocks with the lowest market capitalization (or book value) by nearly 0.60% per month. Thus, GL argue that the size anomaly in bank stocks in the U.S. is really about size, rather than market capitalization. This result is consistent with government guarantees that protect shareholders of large, but not small, financial firms in disaster states.

[7]There is also evidence that government guarantees reduce borrowing costs of large financial institutions. See Acharya, Anginer, and Warburton (2013) for evidence. Office (2014) also finds all 42 of the econometric models that it considered to estimate funding costs implied that large U.S. bank holding companies had significantly lower funding costs than small banks prior to the financial crisis.

because the government absorbed sector wide tail risk. In related work on bank stock returns, Fahlenbrach, Prilmeier, and Stulz (2012) document that banks that incurred substantial losses during previous crises were more likely to incur losses during the recent crisis. If some banks benefit from greater perceived tail risk subsidy, they have an incentive to load up on this type of risk.[8]

The paper is organized as follows. Section 2 describes the dataset, and explains how we construct portfolios of financial firms sorted by size as measured by market capitalization and book value. Section 3 establishes a size anomaly in financial stock returns around the world. Section 4 shows that wide large-to-small financial spreads forecast economic downturns. Section 5 relates the size anomaly to a country's legal, business, financial, sovereign, and regulatory environment. Section 6 describes a bailout-augmented dynamic asset pricing model based on Kelly, Lustig, and Van Nieuwerburgh (2016), which delivers pricing relations consistent with our findings.

2 Identifying Financial Institutions in the Data

Our dataset includes the monthly equity returns, market capitalization, total book value of assets, and the market/book ratio for financial firms from 31 countries. The data source is Thomson Reuters Datastream (henceforth TRD). We select countries included in either the Morgan Stanley Capital International (MSCI) Developed or the MSCI Emerging Markets index. We further restrict the sample to countries that report stock returns for at least 40 financial firms. For a country to be part of our sample, we also require that data for equity returns and market capitalization be available for at least three years. The starting year for data for a particular country is determined by the first full year in which the number of financial firms in that country exceeds 40. The ending time for all is December 31, 2013. In all countries, we exclude very small firms as measured by market capitalization by eliminating the 10% of firms with the lowest market capitalization.

In TRD, we identify financial firms using the sector variable. This variable is based on the Worldscope Industry Classification Benchmark (ICB) codes.[9] ICB allocates a company to the sector of ICB codes whose definition most closely coincides with the source of its revenue or the source of the majority of its revenue. In any country, firms with sector values equal to banks, financial services, insurance, or real

[8]In fact, shareholder value maximization requires that they do so, as pointed out by Panageas (2010), who analyzes optimal risk management in the presence of guarantees. Interestingly, Fahlenbrach, Prilmeier, and Stulz (2012) find some evidence that banks whose managers' interests were more aligned with shareholders actually performed more poorly during the recent financial crisis.

[9]ICB classification benchmark codes are also referred to as the FTSE's Global Classification system, because the classification was developed by FTSE Group and Dow Jones Index.

estate investment services are classified as financial firms. In other words, our definition of financial firms includes banks (ICB Sector DS Level 4 code equal to 8350); non-life insurance (ICB Sector DS Level 4 code equal to 8530); life insurance (ICB Sector DS Level 4 code equal to 8570); real estate investment services (ICB Sector DS Level 4 code equal to 8630); and financial services (ICB Sector DS Level 4 code equal to 8770).

We include all financial firms, not just banks, for two reasons. First, there are significant differences across countries in the way banks and financial services firms are organized. In the U.S., firms that own a commercial bank and entities that provide other financial services are almost always classified as bank holding companies. Bank holding companies are, first and foremost, banks; that is their economic function, so restricting the sample to firms with sector values equal to banks seems inappropriate for the U.S. In many other countries, firms that own a commercial bank as well as other financial entities may be classified as banks, financial services, insurance, or real estate investment services firms[10]. Second, in the U.S., the largest financial firms as measured by market capitalization are banks or financial services firms, but in many other countries the largest financial firms may be insurance or real estate investment services firms. For example, the largest financial firm as measured by market capitalization in Australia is AMP, an insurance firm. Similarly, the largest financial firm as measured by market capitalization in Belgium is Ageas, another insurance firm. As a result, we decided to include all financial firms in our sample.

We eliminate all observations where either the name of the firm, price, or market-capitalization data is missing. Observations for firms that are cross-listed in more than one country are kept only in the country of incorporation. For example, stocks for the bank HSBC trade in New York, London, Paris, and Hong Kong. Since HSBC is incorporated in London, in our database, observations for HSBC appear only with United Kingdom as its country. Cross-listed firms and countries of incorporation are identified using the TRD data-item primary quote.

Within a particular country, multiple observations for the same firm within a month (for e.g., for different share classes) are aggregated at the firm level by value-weighting the returns and price-to-book values and aggregating (summing) the market value. For each country for each month, we winsorize the returns at the 5^{th} and 95^{th} percentile levels to remove outliers. Finally, for a given firm, we identify

[10]This is especially true given TRD's classification system. In TRD a firm that owns a commercial bank and an investment bank will be classified as financial services (i.e., ICB Sector DS Level 4 code equal to 8770) if the investment bank accounts for more than 50% of the total revenue of the firm.

pairs of consecutive observations that have total equity returns that exceed 90%, are of the exact same magnitude, but of opposite signs. An example of this would be a firm that has a total equity return of 95% in January 2013 and -95% in February 2013. We conclude that such entries are likely corrupt, and set the return for this firm in January and February 2013 to be missing. All these changes are necessary, given the data quality in TRD.

We can identify delisted firms because even after a firm delists, TRD continues to report its monthly total equity return, market capitalization, and price-to-book as stale values that do not vary. We specify the first month of a stale value series as the month the firm delists. Data for delisted firms are excluded only after the month in which they delist. Thus, for firms that delist in January of any year, we set monthly total equity returns, market capitalization, and price-to-book values as missing starting only in February of that year. This ensures that the returns properly account for delistings. We also exclude data for all firms that are inactive throughout the sample period by assuming that the investor liquidated holdings of that firm at the final listed price. Our results are robust when we assume that the investor lost all its holdings at the time of delisting. In a final step, we remove all observations for which the firm name includes the word fund, mutual fund, income, or income fund. This filter ensures that our results are not driven by mutual funds or other such investment services.

The final dataset consists of 1,418,532 observations across 31 countries. For all observations total equity returns, market capitalization, total book value of returns, and the ratio of price-to-book value of assets are denominated in local currency. We cross-check the TRD files with other providers to ensure that our filters works well to identify financial firms.[11]

Panel A of Table 1 presents the list of countries in our sample and the number of unique financial firms available throughout the sample period in each country. For each country in the sample, the table lists the country classification (developed vs. emerging market), the start year for the data, the number of unique financial firms in our dataset, the percentage of publicly listed firms that are classified as financial firms, and the percentage of financial firm market capitalization as a percentage of total market capitalization in the country. Note the substantial cross-sectional variation in number and size of financial firms across

[11]We compare our list of U.S. financial firms from TRD to the list of the top 100 bank holding companies by total book value of assets compiled by the Federal Deposit Insurance Company. The TRD list includes firms that account for 80.71% of the total book value of assets of the top 100 bank holding companies in the U.S. The FDIC considers Macy's, Nordstrom, Apple Financial Holdings, and United Services Automobile Association as bank holding companies. DataStream (correctly) does not identify these firms as banks or any other kind of financial firm because that is not their primary business function. Similarly, the FDIC identifies BBVA, Deutschebank, HSBC, and Barclays as large U.S. bank holding companies. Our list includes these firms in their country of incorporation but not as bank holding companies incorporated in the U.S.

countries. For example, in Japan and Taiwan, 10% of publicly listed firms are classified as financial firms, but they account for less than 25% of market capitalization, while in Hong Kong, 34% of publicly listed firms are classified as financial firms and they account for approximately 50% of the market capitalization.

The actual number of unique financial firms also varies by country. The U.S. has the largest number of unique financial firms at 3,201 (accounting for 13.16% of total market cap), followed by India at 778 accounting for (9.35% of total market cap) and the United Kingdom at 778 (accounting for 17.85% of total market cap). The South American countries Chile and Peru have the fewest unique financial firms at 67 (accounting for 32.10% of total market cap) and 55 (accounting for 40.16% of total market cap), respectively. On average, financial firms account for nearly 21% of firms and nearly 28% of the market capitalization in our sample of 31 countries.

Next, we build size-sorted portfolios of financial intermediary stocks. For this, we employ the standard portfolio formation strategy of Fama and French (1993). In each month, for each country, we sort all financial firms into deciles according to market capitalization. So, for example, in January 2013, we rank all financial intermediary stocks in each country by market capitalization. In each country stocks of financial firms are then allocated to deciles on the basis of market capitalization. We then calculate the value-weighted returns for each decile for each country for February 2013. In February 2013, we repeat the process to calculate the same returns for March 2013. At the end of this exercise, we have monthly value-weighted returns for each size-sorted portfolio of financial firms, for each country, over the entire sample.[12]

Panel B of Table 1 reports summary statistics for the size-sorted deciles of financial firms. The statistics are averaged across all countries, and separately across developed and emerging markets. *Large* and *small* denote the portfolios of financial firms with the highest and lowest market capitalization, respectively, and LMS denotes the return of large minus small financial firms. Panel B also reports the average number of unique financial firms (N); the average market capitalization of financial firms as a percentage of market capitalization of the entire financial intermediary sector ($\%FCap$); the turnover rate i.e. the probability (in %) that a firm migrates to another portfolio in the subsequent month ($\%Turn$); and the average value-weighted monthly return (Ret) for large and small portfolios. Here, and henceforth, we annualize average returns by multiplying by 12, and express them in percentage by multiplying by 100.

[12]Later, for benchmarking our results to the standard size-anomaly, we also repeat the porfolio formation exercise separately for all non-financial firms in each of the 31 countries to get the monthly value-weighted returns for each size-sorted portfolio of non-financial firms, for each country, over our entire sample.

Firms in the first decile account on average for 0.20% to 0.42% of the market capitalization of the entire financial sector. On the contrary, the largest financial firms account for anywhere between 67% and 76% of the market capitalization of the entire financial sector for emerging and developed markets, respectively. Thus, it appears that, on average, the financial intermediary sector for the 31 countries is concentrated, with the bulk of market capitalization held by the largest financial companies. There are average of 143 unique financial firms in the small portfolio in a given country compared to 46 for the large portfolio. This pattern also holds for the turnover rate – the probability that a small financial firm migrates to another portfolio is only 13%, and the probability that a large financial firm migrates to another portfolio is even lower at just 3%. This evidence is important for our asset pricing tests as it implies that the performance of a portfolio strategy that goes long the large while shorting the small is not driven by portfolio turnover.

The last two columns of panel B show that, on average, large financial firms underperform small financial firms by 7.84% across all countries. This result is statistically significant at the 1% level. The return to the LMS portfolio, which is the difference in the returns to large and small portfolios, is -3.74% for developed markets and even more negative for emerging markets at -14.77%. Note that the wider gap between the performance of small and large financial firms for emerging markets is driven mainly by the small portfolio.

3 The Cost of Equity Capital for Financial Institutions

To estimate financial firm's cost of equity capital, we start by adjusting the portfolio returns for exposure to the standard risk factors that explain cross-sectional variation in average returns on portfolios of non-financial stocks. We find that small financial firms, measured by market capitalization, outperform a benchmark portfolio of stocks, while large financial firms underperform.

3.1 Cost of Equity Capital after Risk Compensation

To evaluate the performance of financial firms, we use the Fama and French (1993) three-factor model. We use `Market`, `SMB`, and `HML` to represent the returns on the three Fama-French stock factors, namely, the market, small minus big, and high minus low, respectively. For each country, we construct local Fama-French factors using data for all publicly listed entities in each country (including financial firms). To construct the `Market` factor in each country, we measure the excess return on the market using the value-weighted return on all stocks in that country minus the return on the one-month U.S. Treasury bill rate (from Ibbotson Associates). For each country, we construct the local size factor (SMB) and the local value factor (HML) using the six value-weighted portfolios of all stocks in that country sorted by size and book-to-market, respectively. Thus our vector of risk factors includes: $\boldsymbol{f}_t = [\texttt{Market}\,\texttt{SMB}\,\texttt{HML}]$.

We estimate the time-series regression of excess returns to large and small portfolios, and their difference, denoted LMS, on the three Fama-French factors, and report the average risk-adjusted returns along with their statistical significance in Table 2. The columns titled `Fin` report the estimates for financial firms. Because there is variation in the characteristics of firms across countries, we directly compare size-sorted portfolios of financial firms to size-sorted portfolios of non-financial firms within the same country. To form the size-sorted portfolios of non-financial firms, we apply the standard Fama and French (1993) portfolio formation strategy to all firms not classified as financial firms within a particular country. The columns titled `Non-fin` report the results for non-financial firms. Finally, the last two columns of the table report the average risk-adjusted performance of portfolios of financial firms relative to non-financial firms.

Panel A reports pooled estimates for all countries.[13] The risk-adjusted return on the portfolio of largest financial firms is -2.41% (annualized) with a t-stat of -2.41 compared to 8.07% (annualized) for the smallest financial firms with a t-stat of 3.75. Thus, the risk-adjusted return to the LMS portfolio for financial firms in our sample is -10.47%, statistically significant at the 1% level. In other words, a zero-cost portfolio that goes long $1 in the portfolio of largest financial firms by market capitalization and short $1 in a portfolio of the smallest financial firms by market capitalization loses 10.47% per year over the entire sample.

The risk-adjusted returns for both large and small non-financial firms are positive at 1.46% and 3.98%, respectively. Thus, the alpha (risk-adjusted return) of the LMS for non-financial firms is much less negative at -2.52% and is statistically significant at only the 10% level. We compare the country-level risk-adjusted performance of size-sorted financial and non-financial firms in Figure 2. Taken together, the LMS portfolio for financial firms delivers a risk-adjusted return that is approximately 8% lower than the LMS portfolio of non-financial firms (the solid black line in Figure 2). Nearly half of this occurs because large financial firms underperform large non-financial firms by 3.86%. Thus, across 31 countries, stocks of large financial firms seem consistently overpriced compared to a benchmark of non-financial firms of the same size, even

[13] Table A1 and Figure A1 in Appendix C report the results for individual country estimates.

after adjusting for exposure to standard risk factors.

Panels B and Panel C of Table 2 report estimates for data pooled separately for developed and emerging markets. The risk-adjusted return to the LMS portfolio for financial firms in developed markets at -9.47%, is comparable to that for emerging markets at -13.82%. The overpricing of stocks of large financial firms relative to stocks of large non-financial firms is also comparable across developed and emerging markets at nearly -4.31% and -3.70%, respectively.[14]

Table 3 evaluates the performance of the large portfolio of financial firms in terms of specific businesses. That is, for each country we separately analyze the returns of size-sorted portfolios of banks and financial services firms, insurance firms, and real estate investment services firms as identified by the TRD data-item sector. Panel A reports the results for data pooled across all countries.

Over the full 1980 - 2013 sample, the risk-adjusted return for the largest banks and financial services firms is -2.01%, compared to just -0.29% for the insurers and -2.28% for the largest real estate firms. Over 2000-2013, the top decile of banks and financial services firms loses approximately -3.16% per year in risk-adjusted terms compared to -1.44% for insurance firms (not statistically significant) and -2.07% for real estate firms (only marginally statistically significant).

In developed markets, banks benefit from special provisions: deposit insurance, access to special lending facilities at central banks, and implicit or explicit guarantees to creditors. Insurance and real estate investment firms rarely enjoy the same level of protection. Given this background, it may seem surprising that large real estate investment firms also deliver negative risk-adjusted returns. To understand why large insurance and real estate investment services firms also perform poorly, we separately analyze developed and emerging markets in Panels B and C. Much of the underperformance of developed markets is concentrated in banks. Over 2000-2013, for the subset of developed countries the risk-adjusted return on the largest banks is -6.40% (t-stat of -3.48), compared to -1.35% in insurance firms (not statistically significant) and -1.30% for real estate firms (not statistically significant). Further, while the risk-adjusted return on large banks declines monotonically over time, this is not the case for insurance and real estate firms. For emerging countries, only real estate firms are found to deliver abnormally low average returns of -3.72% over the full sample and in the recent sample (when it loses significance).

A statistically significant loss for a long-short portfolio for financial firms other than banks and financial services can be explained by important differences in the way banks and financial services firms are

[14]The difference between the LMS portfolio of financial and non-financial firms is -6.26% in developed markets, but -12.21% in emerging markets, driven entirely by the risk-adjusted returns of the smallest financial firms in emerging markets.

organized across different countries. In the U.S., firms that own a commercial bank and entities that provide other financial services are almost always classified as bank holding companies. In many other countries, firms that own a commercial bank as well as other financial entities may be classified either as banks, financial services, insurance, or real estate investment services firms. In fact, in TRD, an entity that owns a commercial bank and other subsidiaries would always be classified as a "non-bank" financial intermediary if the commercial bank accounts for less than 50% of its total revenues. Further, in the U.S., the largest financial firms as measured by market capitalization are banks or financial services firms. These are exactly the kind of firms that benefit from implicit government guarantees and are considered too-big-to-fail. In many other countries, the largest financial firms as measured by market capitalization may be insurance or real estate investment service firms.

Tables A2 and A3 in Appendix C provide further results for the largest financial firms or financial firms sorted by the type of business they engage in. Table A2 shows the results for size-sorted portfolios of firms that are classified as banks and financial services firms *only* and Table A3 presents the results for the top three largest commercial bank in each country. When we restrict the sample to just banks and financial services firms, the risk-adjusted return on the LMS portfolio is more negative at -11.37%, again statistically significant at the 1% level or better. Table A3 shows that, when we restrict the sample to just the largest banks in each country, the risk-adjusted returns are on average -5.16% for developed markets and +3.81% for emerging markets.

Thus, it appears there are important differences in the size anomaly across emerging and developed markets. There may also be important cross-country differences in regulatory, bank supervision, and crisis-response policies that may drive differences in the magnitude of the size anomaly across different countries.

3.2 Financials' Cost of Equity Depends on Size

We directly compare the performance of large and small financial firms with similar loadings on standard risk factors. For each country, for each financial intermediary in our sample, we estimate loadings on the three Fama-French factors in a given month using data for the prior 12 months. We roll the regression one month at a time to obtain a time series of factor loadings for each financial intermediary in each country in our sample. Next, in each month, for each country, we sort all financial firms into 10 portfolios by loadings on the SMB factor. We compute the firm Z-score as $Z = std(\beta_{\texttt{Market}}) + std(\beta_{\texttt{HML}})$, where *std* denotes cross-sectional standardization, for each financial intermediary. Finally, in each month, we match a financial firm in the large portfolio to the financial firm in the small portfolio in the same `SMB` decile and with the closest Z-score possible. We form value-weighted returns for all financial firms in the large portfolio and in the small portfolio of matched firms.[15]

At the end of this exercise, we have monthly value-weighted returns for large and small portfolios of financial firms that differ by market capitalization but have similar loadings on the Fama-French size factor, `SMB`. We report the average risk-adjusted returns for the large, matched small, and large minus matched small (LMS) portfolios in Panel A in Table A4 in Appendix C. The LMS portfolio loses about 7.59% in risk-adjusted terms per year over the entire sample. This number, although 2.88% lower than the risk-adjusted number for the size-sorted deciles, is still statistically and economically significant.

In Panel B of Table A4 in Appendix C we present results for financial firms matched on the `Market` factor. That is, we compare the risk-adjusted return for financial firms that differ in market capitalization but have similar market betas. Now the large-minus-small LMS portfolio loses about 10.24% in risk-adjusted terms per year over the entire sample. The loss increases to 12.45% by 2000-2013, which is even higher than the -10.83% reported in Panel A for the same period. Overall, the size anomaly does not appear to be impacted by the loadings on standard risk factors.

Ang, Hodrick, Xing, and Zhang (2009) show that firms with high idiosyncratic volatility earn lower average returns than firms with low idiosyncratic volatility. Baker and Wurgler (2015) have revisited this anomaly in the context of U.S. banks. To make sure that the size anomaly is not merely capturing this spread, we match large financial firms to small financial firms with the closest idiosyncratic volatility, computed as the standard deviation of the residuals in the rolling regression on the three Fama-French factors. Panel C of Table A4 in Appendix C shows that small financial firms still outperform large financial firms with comparable idiosyncratic volatility by 8% on a risk-adjusted basis.

We also carefully compare size-sorted portfolios of financial and non-financial firms (Table A5 in Appendix C). We note that the risk-adjusted returns of the Financial-minus-Non-Financial LMS portfolio have been rather stable over different sample periods at about -8%. Panel A of this table also shows that it is the underperformance of large financial firms that increasingly accounts for a large proportion of the difference between financial and non-financial firms. By 2000-2013, the total spread between financial and non-financial firms is -7.82%, nearly 60% (-4.37%) of which can be traced to firms in the top decile.

[15]When there are no small firms in a given `SMB` decile, we assign the risk-free rate.

The size distribution of financial and non-financial firms can be quite different. To make the results more directly comparable, next we sort all financial and non-financial firms into size bins using the decile breakpoints based on the market capitalization of *all* traded stocks in a country (i.e. both financial and non-financial firms). We then apply these common decile breakpoints to separately form size-sorted portfolios of both financial and non-financial firms. The results are in Panel B of Table A5. Here, by design, the financial and non-financial firms in each portfolio are roughly of the same size. The value-weighted risk-adjusted return for financial firms in the last size bin are now 14.22% lower than those in the first bin. For non-financial firms, the size anomaly is a mere -5.05%. By 2000-2013, this size anomaly for financial firms increases to -14.71% while that for non-financial firms drops to -4.77%. Thus, the anomaly for financial firms is at least three times greater than for non-financial firms.

The results of financial and non-financial firms sorted by book value of assets are in Panel C of Table A5. Market capitalization measures size, but it also measures expected returns. Firms that generate more cash flow will tend to have higher market capitalization, but firms with lower expected returns, holding cash flows constant, may also have higher market capitalization. Of course, this argument does not apply to other measures of size such as book value. For example, while market cap sorts are likely to be picking up liquidity effects, book sorts are likely not to. A priori, there is no reason to expect a relation between book values and expected returns. Berk (1997) thus argues that there should be a relation between expected returns and market capitalization.

Panel C shows a similar pattern in risk-adjusted returns when sorting by book value of assets to the pattern when sorting by market capitalization; it is in fact even stronger than the one documented in Panel A. For non-financial firms, there is no evidence of a size anomaly when firms are sorted by book value of assets. For non-financial firms, the value-weighted risk-adjusted return on the large portfolio is 5.51% *higher* than that on the small portfolio. As a result, the spread between the LMS portfolio of financial and non-financial firms is now -14.44%. The sort by book value reveals that for financial firms actual size as measured by book value seems to be a key determinant of returns. That is, larger financial firms have negative abnormal returns.[16]

[16] Table A6 in Appendix C confirms this evidence when we run the standard characteristics regressions separately for financial firms, banks, and non-financial firms for all countries in the sample. For financial firms, when we run a cross-sectional regression of average annual returns on firm characteristics (log of market capitalization and log of book value of assets), we obtain a negative coefficient for log book value (-5.20%) as well as for market capitalization (-5.16%) both statistically significant at the 1% level. When we include both log book value and market capitalization, however, the coefficient on book value for financial firms is at least four times higher than the coefficient on market value. Further, the coefficient on market capitalization is not statistically significant at conventional levels. These results suggest that a 100% increase in the book value of financial firms above the sample average reduces annual returns by nearly 400 basis points for

As a final check, we also compare the risk-adjusted return on large financial firms and a set of large non-financial firms that are similar along various dimensions of risk. Analogous to Table A4 we match large financial firms to large non-financial firms according to loadings on the `SMB` factor or idiosyncratic volatility. In untabulated results, we find that large non-financial firms still significantly underperform large non-financial firms on a risk-adjusted basis by -6.50% (when matched by loadings on `SMB`) and by -3.50% (when matched by idiosyncratic volatility).

3.3 Robustness

We carry out a battery of additional tests to check that the size anomaly for financial firms is robust to a number of changes in experiment design and specification. We confirm that the baseline results are robust to the use of delisting returns, alternative winsorization schemes, sorting techniques, equal-weighted returns, and risk factors.

Delisting returns: Accounting for delisting returns is important, as research shows that the extent of empirical asset pricing anomalies can be sensitive to the treatment of delisting returns. Adjusting for delisting returns is also important if delisting rates for financial firms are different from those of non-financial firms, and if delisting rates are a function of firm size.[17]

To see whether our results are robust to delisting returns, we begin by identifying delisted firms in TRD. We can take advantage of the fact that even after a firm delists, TRD continues to report its monthly total equity return and market capitalization as a stale value that does not vary. We then impute a -100% return to the stock return of all delisted firms so identified. The imputation of a -100% return in this case is equivalent to assuming that all delistings are on account of financial distress or bankruptcy.[18]

We use this new data series (with the -100% imputed returns), to form size-sorted portfolios (sepa-

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a typical financial firm, holding market capitalization fixed.
The columns titled banks in Table A6 show that a similar effect pertains for banks. For banks, size measured by both book value and market capitalization is negatively correlated with returns. Once we control for book value, however, the relation between size as measured by market capitalization and returns is not statistically significant. In most cases the coefficient on book value is at least nine times higher than the coefficient on market capitalization.
The last column reports the results for non-financial firms. For non-financial firms, size as measured by market capitalization drives out any relationship between book value and returns. Over the entire sample the coefficient on market capitalization is nearly twice as high as the coefficient on book value, although neither coefficient is statistically significant. Overall, size explains less than 2% of the variation in annual returns for non-financial firms but nearly 5% of the variation in returns of financial firms and banks in our sample.

[17]For example, Gandhi and Lustig (2015) show that in the U.S., small banks are delisted ten times more than large banks.

[18]Clearly the assumption that all firms delist for financial distress is a strong one. Beaver, McNichols, and Price (2007) analyze reasons for delisted firms in the stock return dataset provided by the Center for Research in Security Prices and find that more than half the delistings are on account of mergers and acquisitions not related to financial distress.

rately) for financial and non-financial firms in each country. Table A7 in Appendix C shows that delisting returns barely impact our result. The return on the large-minus-small LMS portfolio for financial firms improves only slightly from -10.47% in Table 2 to -9.11% in Table A7 and remains statistically significant at the 1% level or better.

Winsorization: In our baseline results, given the data quality in TRD, we winsorize raw data for stock returns from TRD at the 5^{th} and 95^{th} percentile. There is a chance that winsorization at these levels is a severe response and may exclude valid return observations that could substantially impact the results.

Panel A of Table A8 presents the results with the data winsorized at the 1^{st} and 99^{th} percentile levels. The risk-adjusted return on the portfolio of largest financial firms is -2.28% with a t-stat of -2.22 compared to -2.41% with a t-stat of -2.41 in Table 2. The risk-adjusted return to the LMS portfolio for financial firms is still large and negative at -18.96% (statistically significant at the 1% level). The risk-adjusted returns for both large and small non-financial firms are positive at 1.13% and 10.76%, respectively. Finally, the alpha of the LMS portfolio for financial firms is 9.33% lower than the α of the LMS portfolio of non-financial firms.

Accounting for the January effect: Reinganum (1983) shows that small firms experience high returns in January and exceptionally high returns during the first few trading days in January. Keim (1983) also shows that the relation between size and abnormal returns is more pronounced in January than in any other month; nearly 50% of the size effect is driven by abnormal returns in January. To ensure that the January effect does not drive the fact that large financial firms underperform small financial firms, Panel B of Table A8 presents risk-adjusted returns for data pooled across all countries but after excluding all returns for January in each year over the sample period. The alpha of the LMS portfolio for financial firms is -6.91% lower than the α of the LMS portfolio of non-financial firms, which is only 100 basis points lower.

Equal-weighted versus value-weighted returns: Our results are also unchanged when we use either value-weighted or equal-weighted portfolio returns. In Panel C of Table A8, the risk-adjusted return on the equal-weighted portfolio of the largest financial firms is -1.81%. The risk-adjusted return to the LMS equal-weighted portfolio for financial firms is still high and negative at -11.81% (statistically significant at the 1% level). Finally, the alpha of the LMS equal-weighted portfolio for financial firms is 8.51% less negative than the α of the LMS portfolio of non-financial firms.

Sub-sample analysis: We examine the time variation in the size of the risk-adjusted performance to the LMS portfolio and report average risk-adjusted returns computed using the three-factor Fama-French 1993 model over different subsamples in Panel A of Table A9 in Appendix C. The first two columns report estimates for the longest available sample for each country, and coincide with those in Panel A of Table 2. The next two columns are for 1990-2013, and the last two columns are for 2000-2013.

The loss on LMS portfolio of financial firms increases to 10.84% over 1990-2013 and to 10.83% over 2000-2013. The progressively more negative performance of LMS is attributable to a worsening in underperformance of the largest financial firms over time from -2.41% for the full sample to -3.00% for 2000-2013. The small portfolio, by contrast, consistently outperforms the benchmark portfolio of stocks by about 8% in all periods.

Returns denominated in U.S. dollars: Panel B of Table A9 shows the results for returns denominated in U.S. dollars using the U.S., the regional, or the global Fama-French factors to risk-adjust returns. The regional factors are available for 4 regions: Asia, Japan, Europe, and North America. We apply the corresponding regional factors when we analyze returns denominated in U.S. dollars for countries located in each region. Finally, we also use the global Fama-French factors (data available from Kenneth French's website). Panel B of Table A9 shows that whatever the factor model, the LMS portfolio of financial firms loses at least 10% (approximately) over the entire sample.

Additional risk factors: We test if our results are robust to the inclusion of additional risk factors such as "betting against beta" (BAB) factor from Frazzini and Pedersen (2014), a co-skewness factor from Harvey and Siddique (2000), and the idiosyncratic volatility factor of Ang, Hodrick, Xing, and Zhang (2009). We control for the BAB factor because larger financial firms are more levered and hence higher market betas are imputed to large financial intermediary stock portfolios. Frazzini and Pedersen (2014) show that high beta assets are associated with low average risk-adjusted returns. They also document that a long-short portfolio that goes long high-beta stocks and short low-beta stocks generates significantly negative risk-adjusted returns. Baker and Wurgler (2015) also argue that a low-risk anomaly is present in U.S. banks and could be linked to degree of leverage.

In addition, we control for the co-skewness factor because by granting shareholders of large financial firms a menu of out-of-the money put options, the government reduces the negative co-skewness of large financial intermediary stock returns, and Harvey and Siddique (2000) already show that co-skewness is priced in the cross-section of U.S. stock returns. We follow the procedure in Harvey and Siddique to construct the traded co-skewness factor for each country in our sample.

Finally, we construct a volatility factor as the return to a portfolio that goes long stocks of financial firms in the bottom decile of idiosyncratic volatility and short the stocks of financial firms in the top decile of idiosyncratic volatility.

Panel C of Table A9 shows estimates for average risk-adjusted returns for the augmented five-factor model. As is clear from the table, our results are essentially unchanged. The annual return on a portfolio that goes long $1 in a portfolio of large financial firms and short $1 in a portfolio of small financial firms is still large, negative, and statistically significant. The loss on this portfolio is 10.94% (11.03% in the most recent sample) when these additional risk factors are included, and is still statistically significant at conventional levels.

Results for the largest financial firms: Finally, we focus on the very largest firms in each country. We present results for the value-weighted portfolio of the top n financial firms in each country in Panel D of Table A9. Each row corresponds to a distinct value of n, 3, 5, or 10. Over the full sample, a significant share of the negative alpha on the tenth decile is due to the very largest financial firms. The top three financial firms by size account for nearly 67% of the risk-adjusted return for the largest financial firms. The loss for the largest three financial firms increases to -2.72% over the 2000-2013 sample, compared to -2.16% for the largest then financial firms. Thus, over 2000-2013, the risk-adjusted return for the top 3, 5, or 10 financial firms by size across all countries accounts for 90%, 80%, or 70% of the risk-adjusted return of all financial firms in the tenth decile.

3.4 Cost of Implicit Guarantees

If the differences in the average risk-adjusted returns of large and small financial firms is the result of financial crisis tail risk insurance offered to large (but not small) financial firms, our methodology allows us to compute a direct estimate of this insurance on the cost of equity capital of financial firms. To this end, we first regress the returns to LMS on the three Fama and French (1993) stock risk factors for each country, and store the resulting abnormal return or alpha. Next, for each country, we multiply this alpha by the average market capitalization of firms in the large portfolio. We then normalize this quantity by the gross domestic product (GDP) of the country as of December 2013.

Table A10 in Appendix C reports the average of this normalized quantity across different groups and time periods. All entries in the table are negative, meaning that the total effect is consistent with tail risk subsidy. Panel A shows estimates averaged across all countries. We see that over the entire sample, the subsidy to the cost of equity capital for large financial firms is 2.68% of GDP. By 2000-2013, this figure increases to as much as 3.45% of GDP.

In Panel B, we report averages separately for developed and emerging markets. The subsidy in developed markets is always greater than in emerging markets. In the most recent sample, the difference is quite significant, with developed markets averaging 5.39% of GDP compared to 1.08% figure for emerging countries. In USD terms, these differences are even more stark if we consider that the average GDP of developed markets in our sample is $2,270 billion in December 2013 compared to only $206.63 billion for emerging markets.

Finally, Panel C collects averages by geographical region. Note that the subsidy is the highest for Asia Pacific countries, followed by Americas, the Middle East, and Africa. In USD terms, the subsidy is highest for Asia ($1,356 billion), and for the Americas ($759 billion), and lagged by Europe ($129 billion) and the Middle East ($17 billion).

It is worth noting that our estimates of the subsidy measure only impact of tail risk insurance on the cost of equity capital. As financial institutions are highly levered, even if the direct effect on the overall cost of capital may be minute, the indirect effect would note be because shareholders are last in line, the implied subsidy to other bank creditors would be even greater.

4 Financials' Cost of Equity Capital and the Probability of a Financial Crisis

A financial crisis is typically defined as an event during which a country's financial sector experiences runs and sharp increases in financial sector default rates accompanied by large losses of capital that result in public intervention, bankrutpcy, or the forced merger of financial institutions. In the event of a financial crisis, governments and regulators often provide an implicit guarantee to shareholders of large financial institutions, but not to those of small financial institutions. This is true not only for the U.S. but also for most developed and emerging markets included in our samples.[19]

The presence of implicit government guarantees would induce a systematic link between a financial firms' exposure to tail risk (associated with the risk of a financial crisis) and firm size. The model we define below suggests that these implicit guarantees will impact the expected returns of size-sorted portfolios of financial firms. If a financial firm is considered too-big-to-fail, then its expected return is lower in equilibrium than a smaller financial firm holding the exact same assets. Further, variation in the probability of financial crisis will drive variation in the expected returns of size-sorted portfolios of financial firms over time. In other words, not only are the expected returns of large financial firms lower than those of small financial firms, but the expected return gap between large and small financial firms is directly proportional to the probability of a financial disaster.

Historically, the probability of a financial disaster increases during economic and market downturns. In the U.S. data, there is a strong connection between the business cycle and the incidence of financial crisis.[20] Therefore, we next study the link between the differences in the returns of large and small financial firms and the potential risk of a future economic downturn. Our hypothesis is that if the size anomaly is indeed driven by implicit guarantees, an increase in the expected return gap between small and large financial firms is, on average, associated with an increase in the probability of an economic or market downturn (hence a financial crisis) in the near future. As long as financial crises are not perfectly correlated across countries, our international panel structure enhances identification and increases the power of our test.

Table 4 presents the estimates from a panel conditional fixed-effect logit regression. The dependent variable is a dummy variable that takes a value of 1 when the H-month ahead return on the aggregate stock market index (for Panel A) or the H-month ahead growth rate of gross domestic product (for Panel B) is below the 10th percentile level, with $H = \{3, 6, 9, 12\}$. The independent variable is the monthly value-weighted dividend yield of large over small financial firms.

We expect that as the probability of a financial crisis increases, the risk premium on large-minus-small LMS increases; i.e., the expected return on the LMS portfolio becomes more negative. This in turn implies that the difference between the dividend yield of large and small financial firms should become

[19] For example, Laeven and Valencia (2008) document that in most countries, an emerging financial crisis results in direct liquidity injection, large-scale government intervention, or even blanket guarantees extended to customers, creditors, and shareholders of large financial institutions.

[20] See, for example, Romer and Romer (2015) among others for the link between financial crisis and economic and market downturns.

more negative. That is, the sign on the monthly value-weighted dividend yield of large over small financial firms should be negative. This is exactly what we see in the data.

An increase in the expected return gap between small and large banks indicates an increase in the probability of a drop in the stock market or a drop in GDP. A 1% increase in the dividend yield gap increases the odds of a 10% drop in the stock market over the next three months by nearly 13% and that of a 10% drop in GDP by approximately 10%. Thus, the size anomaly in financial firm returns appears to be a reliable measure of future economic downturns, and is sensitive to changes in the probability of a financial crisis in the near future. This evidence is consistent with the hypothesis that the existence of implicit government guarantees to shareholders of large financial firms drives the observed size anomaly in size-sorted portfolios of financial firms.

If large financial institutions benefit from government implicit guarantees, we should also expect that the performance of the LMS portfolio, while negative on average, should improve (i.e. turn positive) during crisis periods when large firms are in fact shielded. We investigate whether this is indeed the case in Table 5, which collects the returns to the LMS portfolio during an economic or financial crisis.

As before, for each country in our sample, we identify an economic or a financial crisis as a quarter during which the GDP or stock market return falls below the 10th percentile for that country. If there are consecutive quarters that meet this criterion in any country, they are counted as one incident of an economic or financial crisis. For each country, for each economic or financial crisis, we consider a $100 investment in the long-short LMS at the start of the crisis, and measure its cumulative performance at the end of the crisis.

Each row in Panel A of the table displays the average performance of this investment over all economic and financial crisis in each country in our sample. In Panel B, we report the average performance of this long-short portfolio over all crises across all countries, developed markets only, and emerging markets only.

Table 5 shows that such a portfolio on average gains 6% during an economic crisis. Thus, the LMS portfolio is sensitive to large slowdowns in the economy (i.e., performance improves during economic or financial contractions). We attribute this result to differences in shareholder recovery rates on these portfolios under economic or financial distress. During economic or financial crisis, large financial firms fare much better even though they are typically more leveraged than small financial firms. In other words, as the probability of a financial disaster increases (during economic or financial crisis), the expected return gap between large and small financial firms grows, and large financial firms do much better than smaller financial firms (in realized returns).

The performance of the LMS portfolio during an economic and financial crisis may be attributed partly to differences in delisting rates. It is well established that governments and regulators, due to the implicit bailout guarantee, are not willing to let large financial firms fail, even if they regularly allow individual small financial firms to go under. Therefore, the last three columns in Table 5 report the delisting rates of firms within the top and bottom 10th percentile in each country, as a percentage of total number of firms in these portfolios at the start of the economic or financial crisis. The table shows that on average, 0.86% of the firms in the bottom 10^{th} decile fail during an economic crisis, while the corresponding number for the top 10^{th} decile is only 0.20%. These numbers imply that in each quarter in which a given country in our sample is in an economic or a financial crisis, on average 2 small financial firms fail. The total number of crisis quarters across all 31 countries in our sample is 331. This implies that on average 662 small financial firms delisted over all financial crises across the 31 countries in our sample. The corresponding number for large financial firms is 30.

Table 5 also highlight clear differences between developed and emerging markets in the crisis performance of the LMS portfolio. While for developed markets, the LMS portfolio on average gains 16%, for emerging markets this portfolios loses approximately 2% of its value. These differences suggest that there may be significant cross-sectional (cross-country) differences in the size anomaly in the financial sector, which result from the implicit bailout guarantee provided by regulators. These differences may be closely related to the legal, economic, policy, regulatory, and institutional frameworks in a particular country.

5 Determinants of Financials' Cost of Equity Capital

So far, we have established that the size anomaly for financial firms is very different from that for non-financial firms and is also distinct from the market capitalization effect first documented by Banz (1981). We have also shown that the differences in risk-adjusted returns for financial firms cannot be imputed to differences in exposures to standard risk factors. We exploit the cross-sectional dimension of the dataset to lend further support to the claim that this anomaly is related to the presence of implicit bailout guarantees to large financial institutions.

We begin by relating the extent of financial sector tail risk insurance, as captured by the difference in the average risk-adjusted return on the size-sorted portfolios of financial firms for each country to the country's legal, business, financial, and regulatory framework. If the size anomaly for financial firms is merely an extension of the market capitalization effects documented in the literature for non-financial firms, then the time-series/cross-sectional variation in the extent of the anomaly should not be related to variables that measure the institutional environment. The converse is that, if the underperformance of large financial firms indeed occurs because of explicit or implicit guarantees extended to large but not small financial firms, we expect a more severe anomaly (a more negative result) when a country's regulatory, policy, and institutional framework makes bailouts more likely in the event of a financial crisis. We also expect a greater anomaly in countries where financial firms respond rationally to a lower cost of capital (due to implicit guarantees) by increasing risk.

We use a standard panel regression framework to study the relation between the size anomaly in financial stock returns and a country's legal, business, financial, and regulatory framework. The dependent variable in each case is the large-minus-small LMS returns (i.e., the difference in the risk-adjusted return to large minus small financial firms), computed using data for all financial firms over 2-year non-overlapping windows. While all the results use data for all financial firms to compute LMS, most of our results are robust either to using data for just banks or to using the difference in the risk-adjusted returns of financial and non-financial firms.

Note that our panel regressions include country fixed effects and time-fixed effects where applicable. In all the panel regressions we almost always include country fixed effects and also account for time fixed effects whenever there is sufficient time-series and cross-sectional variation in the dependent variables.

5.1 Legal Environment

Table 6 examines the relation between the size anomaly in financial stock returns and the legal environment in a country using a standard panel regression framework. The independent variables are a set of dummy variables that take for the origin of the legal system in a country a value of either British (L_{UK}), French (L_{FR}), German (L_{GR}), or Scandinavian (L_{SC}), and zero otherwise.

As explanatory variables we also include an index of property right index ($Property$), an index of how left-leaning the federal (central) government is ($Left$), and an index of government integrity in each country in our sample ($Integrity$). Higher values of $Property$, $Left$, and $Integrity$ imply that the country has stronger property rights, a more left-leaning federal government, and a lower levels of corruption (or perception of corruption).[21]

[21] The data for the legal origin come from La Porta, Lopez-de Silanes, Shleifer, and Vishny (2000); for *Property* and

Each column in Table 6 presents the results for a separate specification of the panel regression, where the dependent variables are standardized to mean zero and standard deviation one. Each regression includes time fixed effects and t-statistics are based on robust standard errors.

The results in Table 6 indicate more of an anomaly (i.e., the risk-adjusted return on LMS financial firms is more negative) in countries with British legal origin (common law countries), and less in countries with Scandinavian legal origin. In other words, investors in countries operating under common law perceive a higher probability of bailout of large financial institutions than those in countries operating under other legal systems.

At first glance, this result is surprising because La Porta, Lopez-De-Silanes, and Shleifer (2002), for example, show that governments in countries with French, German, Scandinavian, or socialist legal systems are more likely to intervene in economic activity than governments in countries with a common law legal system. When it comes to financial firms, however, the opposite seems to be true – market participants anticipate that governments in countries with a common law legal system will intervene on behalf of shareholders of large financial firms more often or to a greater extent than governments in countries with other kinds of legal systems. Yet, the more negative α for common law countries is consistent with the notion that common law countries are perceived to offer better protection to shareholders. As a result, in a bailout, shareholders are less likely to be wiped out.

There is yet another reason why the LMS α can be expected to be higher in common law countries. Implicit or explicit guarantees of large financial firms, coupled with stock-based compensation plans for CEOs, may motivate managers to try to increase shareholder wealth, in part by increasing risk. In most common law countries, stock-based compensation plans are common, and common law systems usually place little limits on higher pay for CEOs. For example, Gomez-Mejia and Werner (2008) find that there are few limits on higher pay for CEOs in common law countries because these systems are less prescriptive. In most other legal systems (especially civil law systems), there are legal limits on CEO compensation. For example, in both Argentina and the Philippines CEO pay is limited by law. CEO compensation must also meet an unstated "reasonability" criteria in many other countries including Germany.

Any institutional feature that credibly puts investors of large financial firms at risk of loss would likely reduce the LMS α. Stern and Feldman (2004) argue that although expectations of bailouts cannot be eliminated, they can be reduced or better managed through a credible commitment by regulators to

Integrity from the Heritage Foundation; and for *Left* the World Statesman (http:\www.worldstatesman.com).

impose losses on investors. They further argue that strong property rights along with other reforms can help ensure that excessive risk taking does not occur in the financial sector, thereby reducing the need to bail out financial institutions. These reforms can also help reduce the moral hazard incentives for excessive risk taking created by the government safety net even if large financial firms are not treated differently from small financial firms. Consistent with this view, we find that the overpricing of large financial firms (relative to small financial firms) is less severe in countries with stronger property rights.

Finally, Table 6 also shows a smaller LMS α in countries where government integrity is high and there is less corruption. This result can be understood if interpreted in light of the classic principal-agent problem. Regulators are ultimately agents of taxpayers, as any losses on account of bailouts are borne by taxpayers, but regulators may have incentives that differ from those of taxpayers. That is, regulators and governments may pursue a too-big-to-fail (TBTF) policy for reason of personal gains (Mishkin (2006) and Kane (1989, 1991)). In this case, guarantees may be provided to large financial firms not because of any wider economic benefits, but because failure on a regulator's watch is too personally important, or because regulators may accede to implicit industry pressure in order to be in line for favorable private-sector jobs later. If higher government integrity (less corruption) makes such principal-agent violations between regulators and taxpayers,this should reduce the likelihood of bailouts. This is exactly what the result in Table 6 suggests.

5.2 Business Environment

Table 7 examines the relation between the size anomaly in financial stock returns and a country's business environment. The estimation framework is the same as in Table 6, except that some regressors exhibit enough within-country variability that allows us to include country fixed effects. The independent variables are an index that measures the strength of corporate disclosure ($Disclose$) and an index that measures the strength of corporate governance ($Govern$). Higher values of these indices indicate stronger disclosure and corporate governance requirements.

We include as explanatory variables the number of publicly listed firms in the country ($Nfirm$); an index that measures the ability of the government to formulate and implement sound business regulations ($Regln$); the strength of bankruptcy resolution measured by looking at average recovery rates, time taken to resolve bankruptcy cases, outcomes, and cost of bankruptcy in a country ($Bankrupt$); and an index that measures the extent of economic and political globalization ($Global$). Higher values in this case indicate a country's tighter regulation of businesses, stronger bankruptcy mechanisms, and more globally connected economy. We relate the α to an index that measures the risk of appropriation by the government ($ExpropRisk$) in a country. We also include variables that measure the size and importance of stock markets in a country such as the overall market capitalization of all publicly listed firms in the country ($Mktcap$), the average annual volatility of the primary stock market index ($StockVol$), and the average annual return on an index of all publicly traded firms in the country ($StockRet$).

The results in Table 7 indicate less of a difference in the risk-adjusted return on LMS financial firms in countries with stronger corporate disclosure and corporate governance requirements, in countries with tighter business regulations, and in countries that are economically and globally more connected with other countries. The LMS α is larger (more negative), however, in countries with tighter bankruptcy laws and when there is a higher risk of government expropriation, and when the stock market is more volatile. Finally, the size of the LMS α does not seem to be significantly related to either number of publicly listed firms, overall stock market size, or the average aggregate stock return.

There is a large literature that analyzes the effect of corporate disclosure and governance policies on the financial outcomes for firms. To the extent that the size anomaly reflects implicit bailout guarantees in financial disasters, the government essentially subsidizes large financial firms to take on tail risk. Any external mechanism that counters such risk-taking behavior of financial firms would attenuate the anomaly. Acharya, Amihud, and Litov (2011) show that stronger disclosure and corporate governance rules are such mechanisms. They show that firms in countries with strong corporate governance do not take as much risk as compared to firms in other countries. A negative association between corporate governance and risk taking is also suggested by Laeven (2002), who shows that financial firms with more concentrated ownership take more risks than financial firms with diverse ownership.

Thus, the fact the extent of the size anomaly is inversely related to corporate governance is consistent with the hypothesis that the anomaly is a manifestation of implicit government guarantees. The strength of general disclosure laws can also affect the incentives of policymakers to engage in providing explicit or implicit guarantees to TBTF financial firms. If regulators and policymakers know that their involvement with a bailout of uninsured investors will receive considerable publicity and review, they might be less willing to provide one.

Stronger supervision and regulation of business and financial firms in particular can reduce the expectations of TBTF coverage. Stronger regulation could also make bailouts less likely if it reduces risks taken and the subsequent losses that the failure of a financial firm imposes on taxpayers. In addition, a strong regulatory framework, could also reduce risk taking by increasing the market discipline of financial firms. For these reasons, it is not surprising that the coefficient on *Regln* is positive and economically and statistically significant – stronger regulations reduce the incidence of distress and the likelihood of bailout by regulators.

Table 7 indicates (somewhat surprisingly) that the LMS α is more negative in countries with stronger creditor rights, as captured by *Bankrupt* whose coefficient is negative and statistically significant. Ex-ante one might expect stronger creditor rights to reduce the incentive of financial firms to take on unnecessary risk (asset-substitution). Yet, Houston, Lin, Lin, and Ma (2010) in a study of 69 countries show that stronger creditor rights are in fact correlated with higher risk. They find that stronger creditor rights encourage financial firms to assume more risk, and that unnecessary risk taking significantly increases the likelihood of financial crisis in the future. If large financial firms require bailout in the event of subsequent financial crisis, stronger creditor rights should be related to a greater difference in the risk-adjusted returns of large and small financial firms. This is exactly what we see in Table 7.

The positive coefficient on *Global* is quite striking. It indicates less of a difference between the risk-adjusted performance of large and small financial firms in countries that are more politically and economically connected with other countries. Obstfeld (1998) examines how the extent of globalization impacts the national policy choices of a government and regulators. He finds that globalization has the beneficial side-effect of disciplining governments, directing them toward sustainable budgets and price sustainability. This implies that globalization might exert a similar downward pressure on fiscal profligacy in financial firms. Thus, globalization (and a measure of openness) of an economy may give regulators and policy-makers an incentive to refrain from protection of insolvent financial firms, thus reducing the likelihood of bailouts.

Table 7 also shows a higher LMS α in countries with a higher risk of expropriation, indicating that market participants expect shareholders of large financial institutions are more likely to be bailed out in the event of a financial crisis. This result is a bit puzzling, if the higher risk of expropriation implies that governments and regulators are more likely to let shareholders of publicly listed firms (and of financial firms in particular) be wiped out in the event of a financial crisis. That is, if expropriation is associated with a higher probability that governments and regulators will take private property away from owners (shareholders) of financial firms, the TBTF guarantees should not be priced in stock returns. On the other hand, if market participants believe that governments and regulators are more likely to intervene on behalf of shareholders of large financial firms in countries with a higher risk of expropriation, then our results make sense.

Finally, the coefficient on stock market volatility $StockVol$ is -4.10 (statistically significant at the 5% level), indicating that higher volatility (in bad times) is associated with a greater gap in the risk-adjusted returns of large and small financial firms. Standard neo-classical models (such as Cochrane (2008)) suggest that improved macroeconomic conditions should be negatively correlated with stock market volatility, that is, stock market volatility increases in bad times. The model in section 6 above also suggests that in bad times, as the probability of financial crisis increases, the expected returns gap between size-sorted portfolios of financial firms widens.

5.3 Financial Environment

Table 8 examines the relation between the size anomaly in financial stock returns and a country's financial sector environment. The independent variables are size of the financial sector in a country as measured by the log of the total number of branches of financial firms ($Branches$) and the ratio of total financial sector demand deposits to GDP ($Deposits$). We also include variables that measure the financial performance of the financial sector: the ratio of non-performing loans to total loans ($Nonperform$); the ratio of total financial sector liquid assets (e.g., cash, liquid securities) to total book value of assets ($Liquidity$); the return on equity of financial firms ($Profit$); the ratio of defaulted loans to total loans ($Defaults$); and leverage as measured by the total capital-to-assets ratio ($Leverage$). Variables that measure the characteristics of the financial sector and the type of consumers that use financial services include the total depth of public debt markets in a country ($BondDepth$) and the percentage of financial claims held by non-residents ($Foreign$). We include a dummy variable that equals 1 if a country has deposit insurance and the degree of concentration/competitition in the financial sector as a percentage of total assets held by the top 3 ($Top3$) and top 5 largest financial firms ($Top5$). We also include measures of credit provided by financial firms to private entities ($PvtCredit$) and to government-owned entities ($GovCredit$).

Four key results emerge from the analysis in Table 8. First, there is a greater risk-adjusted difference between the returns of large and small financial firms, the more dependent a country is on the financial sector, as measured by the number of financial firm branches in the country and the ratio of total demand deposits-to-GDP. The coefficients on these variables are -11.20 and -6.35, resepectively and are statistically significant at the 10% level or better. This result is consistent with the fact that regulators and governments are more likely to provide implicit and explicit guarantees to financial firms in countries where a higher percentage of the population accesses formal financial institutions.

Poor performance of the financial sector increases the likelihood of a financial crisis and makes it more likely that regulators will likely need to step in to bailout financial institutions that are at the risk of failure. Indeed, we see that the LMS α increases when the ratio of non-performing loans in a country increases, when financial firms are liquidity-constrained, when financial firms suffer from low profitability, or when there is an increase in the percentage of non-performing assets (defaulted loans) held by financial firms.

Surprisingly, the overall leverage of the financial sector does not affect the likelihood of bailouts as perceived by the shareholders of large financial firms. The coefficient on *Leverage* is not statistically significant and has the wrong sign. An increase in the capital held by financial firms indicates that bailouts are more likely (i.e., LMS α is more negative). This result is consistent with Jordà, Richter, Schularick, and Taylor (2017), who show that the amount of capital held by financial firms is not a significant predictor of financial crisis in the near future.

Third, the size anomaly is lower in countries where bond markets are more developed and where a higher percentage of claims on financial firms are held by foreigners. In contrast, the LMS α is higher where the financial sector is more concentrated (and less competitive), as measured by the percentage of financial sector assets held by the three or five largest financial firms in the country. Surprisingly, the degree of government ownership of financial firms and the presence (or absence) of deposit insurance does not seem to be statistically significantly related to the likelihood of bailouts as perceived by shareholders.

The fact that bond market development and foreign ownership of financial firm claims reduce LMS α is not surprising. If borrowers in a particular country have easy access to public debt markets, they are less likely to be dependent on financial firms. This in turn makes financial firms less important for an economy, and regulators more unwilling to expend valuable resources in an attempt to save large financial firms.

The fact that financial firm concentration increases the size anomaly for financial firms is consistent with Boyd and De Nicolo (2005), who show that concentrated (less competitive) markets induce financial firms to assume greater risk. Boyd and De Nicolo (2005) find a positive relation between concentration and financial firm fragility and thus the probability of systemic distress. Similarly, Caminal and Matutes

(2002) show that less competition can lead to less credit rationing, larger loans, and a higher probability of failure. Concentrated financial systems generally have fewer financial firms and render policymakers more concerned about financing firm failures than when there are only a few financial firms. Thus, financial firms in concentrated systems will tend to receive larger subsidies through implicit "too-important-to-fail" policies that intensify risk-taking incentives and hence increase financial system fragility – this is exactly what we find in the data.

Finally, the relation between credit to private and government entities and shareholder perception of implicit guarantees (as measured by the LMS α) is not statistically significant at conventional levels. Interestingly, the coefficient on $PvtCredit$ is positive and that on $GovCredit$ is negative. Although, the values are not statistically significant, the direction of the relation suggests that financial firms are more likely to be bailed out when they have extended a large amount of credit to either the government or government-owned entities, but not if they are providing credit primarily to private companies.

5.4 Sovereign Environment

In Table 9, we examine the link between the size anomaly in financial stock returns and a country's fiscal and sovereign environment. We capture that environment using the amount of fiscal surplus (as a percentage of GDP) in the country ($Surplus$); the difference in the yield-to-maturity on the long-term bond issued by a country and the yield-to-maturity on the long-term bond issued by the U.S. Treasury ($Spread$); the ratio of central bank balance sheet assets to GDP ($CentBank$); the level of inflation ($Inflation$); and the per-capita GDP in the country. The results indicate a greater size (more negative) in countries with a higher corporate tax rate, a higher ratio of central bank assets-to-GDP, and and a higher per-capita GDP. These findings confirm that governments in better health are more likely to step in and bailout large financial firms in the event of a financial crisis.

The positive and statistically significant coefficient on $Inflation$ in Table 9 also makes sense. Historically, the most severe financial crises are also associated with severe economic contractions. For example, in the U.S., the financial crises of 1857, 1873, 1893, 1907, and 1930-1933 were all accompanied by severe economic contractions. This was also true of the recent credit crisis of 2007-2009. Financial crises almost always involve sharp declines in asset prices and risk of deflation or disinflation. This is precisely when the risk of failure of large financial firms is high.

Finally, table 9 shows a more negative size anomaly, the higher the value of assets held by a country's central bank (as a percentage of GDP). Arguably, a well-equipped, well-financed central bank is needed to provide support to large financial firms in the event of financial crisis, and large financial firms can be supported only by the balance sheet of central banks.

5.5 Regulatory Environment

Finally, Table 10 relates the size anomaly to the response of regulators and policymakers to past financial crises, as measured by the severity of a crisis ($NPLevel$); the cost it imposes on regulators and governments ($Cost$, $LiqSupport$, $NPLevel$); and various variables capturing their response ($SovDebtInc$, $MonetaryExp$, $EntryBarrier$, $Supervision$, $Privatize$, $Reform$, and $Restrict$).

We find a wider risk-adjusted spread between large and small firms when the costs imposed by a recent financial crisis are high. When the loss of output during a financial crisis is high ($Cost$) or when the government provides a large amount of liquidity to financial firms at the peak of the financial crisis ($LiqSupport$), the spread between large and small financial firms widens. Similarly, the spread also widens in an especially severe financial crisis. A substantial increase in the level of non-performing loans (as a percentage of total financial sector loans) indicates the severity of the financial crisis, increases the likelihood of bailouts of large financial firms, and thereby widens the risk-adjusted return spread between large and small financial firms.

Finally, when a financial crisis threatens, regulators and policymakers have two broad approaches available to them. The first, which we call an accommodative approach, recommends that regulators and policymakers support financial firms via various regulatory policies such as open-ended liquidity support, repeated recapitalization, and blanket guarantees to their depositors and creditors. The alternative approach is to restore depositor confidence but to require financial firms to meet standard regulatory rules (such as capital requirements) or face official intervention that includes bankruptcy resolution mechanisms. If a particular country has adopted an accommodative approach to financial crises in the past, investors would anticipate similar intervention in the future as well, and this would be reflected in a greater size anomaly for financial firms.

Table 10 reports that accommodative regulatory policies strengthen investors' belief that large financial firms will be supported in the event of a financial crisis. These beliefs manifest themselves in a wider average risk-adjusted return spread to LMS. If the government had to issue substantial new sovereign debt ($SovDebtInc$), or implement expansionary monetary policies ($MonetaryExp$), the LMS α widens and becomes more negative.

Tighter restrictions on the financial sector in response to a crisis, however, would reduce the possibility that the next financial crisis would require outright support to debtholders and equityholders of large financial firms, and hence diminish the difference in the risk-adjusted returns of large and small financial firms. This is exactly what we find in the data. If financial sector supervision is tightened, if reforms are enacted, and if restrictions are placed on financial sector activities in response to a recent financial crisis, this reduces the likelihood that the next financial crisis would require large transfers from governments and regulators to prevent liquidation of financial firms, and reduces the LMS α.

As a last point, note that an increase in competition in the financial sector is associated with a reduction (and not an increase) in the LMS α. When there are more private and public financial firms in a country (non-government-owned), this is associated with a decline in LMS α by 7.04%, a result that is statistically significant at the 1% level. This result is inconsistent with the conventional view that "excessive competition" can lead to socially undesirable outcomes such as failures, financial crisis, runs, and panics. Instead, this evidence is consistent with Boyd and De Nicolo (2005), who show that a more competitive financial sector makes financial firms less (and not more) risky.

5.6 Placebo Test

We also carry out a placebo test by running all cross-sectional regressions for non-financials. In almost all cases, the same variables are not significantly correlated with the non-financial LMS spread. In some cases, these variables enter significantly with the wrong sign. For example, *Disclose* and *Govern* have opposite signs when the non-financial spread LMS is on the left-hand side. There are some exceptions: the common law dummy L_{UK} and the Scandinavian law dummy L_{SC} in Table 6; and the liquidity variable and the concentration variable $Conc5$ in Table 8 – all enter with the same sign and are statistically significant when the non-financial spread LMS is on the left-hand-side, but the coefficient on L_{SC} and $Conc5$ is at least twice as high for financials. Only the common law dummy L_{UK} (Table 6) and liquidity (Table 8) enter with the same sign and size.

5.7 Summary

We reiterate that if the size anomaly for financial firms is simply the equivalent of that already documented for non-financial firms, ex ante, we should not see any connection between the extent of the anomaly and the legal, business, and regulatory framework in a particular country. In untabulated results, we confirm that these results also hold for just the largest financial firms in a country, and are robust to varying specifications (such as including a dummy variable for just developed markets). Overall, a country's institutional framework captures a substantial fraction of the cross-sectional and time-series variation in the size anomaly in the financial sector, which is tied to the time-varying probability of implicit or explicit government guarantees to large (but not small) financial firms in a country.

6 The Cost of Equity Capital in a Bailout-Augmented Model with Financial Disaster Risk

We provide a simple model of financial crises and bailouts based on Kelly, Lustig, and Van Nieuwerburgh (2016). In the model, financial crises are periods of elevated risk of a financial disaster, modeled following Barro (2006) and Rietz (1988). The critical difference between financial firms and non-financial ones is their susceptibility to runs during financial crises. Historically, runs have been made by depositors, but in the modern financial system they are made by other creditors such as investors in asset-backed commercial paper, repos, and money market mutual funds (see Gorton and Metrick (2009)). This leads us to take financial disasters as a source of aggregate risk. To model the asset pricing impact of financial disasters, we use a version of the Rietz (1988); Longstaff and Piazzesi (2004); Barro (2006) asset pricing model with a time-varying probability of disasters, as developed by Gourio (2008); Gabaix (2012); Wachter (2013). The model features two sources of priced risk: Gaussian risk and financial disaster (tail) risk. We model the collective government guarantee as a floor on the aggregate financial company losses that the government will tolerate in a financial disaster. Through this truncation, the government eliminates part of the sectorwide tail risk, but it does not eliminate idiosyncratic tail risk. Effectively, the government provides a subsidy for insurance against the effects of systemic financial disasters. While non-financial corporations are also subject to the aggregate risk generated by financial disasters, their exposure is more limited and they do not enjoy the collective bailout guarantee that supports the financial sector.[22]

We take the bailout-augmented dynamic asset pricing model of Kelly, Lustig, and Van Nieuwerburgh (2016).

[22] Muir (2016) compares the implications of this class of models to data on financial crises, and finds that risk premiums are not sufficiently responsive prior to these episodes.

6.1 Preferences

We consider a representative agent with Epstein and Zin (1989) preferences over non-durable consumption flows. For any asset return $R_{i,t+1}$, this agent faces the standard Euler equation:

$$
\begin{aligned}
1 &= E_t\left[M_{t+1}R_{i,t+1}\right], && (1)\\
M_{t+1} &= \beta^{\alpha}\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\alpha}{\psi}} R_{a,t+1}^{\alpha-1}, && (2)
\end{aligned}
$$

where $\alpha \equiv \frac{1-\gamma}{1-\frac{1}{\psi}}$, γ measures risk aversion, and ψ is the elasticity of inter-temporal substitution (EIS). The log of the stochastic discount factor (SDF) $m = \log(M)$ is given by:

$$
m_{t+1} = \alpha \log \beta - \frac{\alpha}{\psi}\Delta c_{t+1} + (\alpha - 1)r_{a,t+1}. \tag{3}
$$

All lowercase letters denote logs. We note and use later that $\frac{\alpha}{\psi} + 1 - \alpha = \gamma$.

6.2 Uncertainty

There is a time-varying probability of disaster, p_t. This probability follows an I-state Markov chain. Let Π be the $1 \times I$ steady-state distribution of the Markov chain and $\mathcal{P}$ the $I \times 1$ grid with probability states. The mean disaster probability is $\Pi\mathcal{P}$. The Markov chain is uncorrelated with the other consumption and dividend growth shocks introduced below, although, the volatility of Gaussian consumption and dividend growth risk potentially varies with the Markov state. This allows us to capture higher Gaussian risk in bad states associated with high disaster probabilities.

In state $i \in \{1, 2, \ldots, I\}$, the consumption process (Δc_{t+1}) is given by a standard Gaussian component and a disaster risk component:

$$
\begin{aligned}
\Delta c_{t+1} &= \mu_c + \sigma_{ci}\eta_{t+1}, \quad \text{if no disaster} && (4)\\
\Delta c_{t+1} &= \mu_c + \sigma_{ci}\eta_{t+1} - J^c_{t+1}, \quad \text{if disaster,} && (5)
\end{aligned}
$$

where η is a standard normal random variable, and J^c is a Poisson mixture of normals governing the size of the consumption drop (jump) in the disaster state. We adopt the Backus, Chernov, and Martin (2011) model of consumption disasters. The random variable J^c is a Poisson mixture of normal random variable.

The number of jumps is n with probability $e^{-\omega}\frac{\omega^n}{n!}$. Conditional on n, J^c is normal with mean $(n\theta_c)$ and variance $n\delta_c^2$. Thus, the parameter ω (jump intensity) reflects the average number of jumps, θ_c the mean jump size, and δ_c the dispersion in jump size. Finally, we allow for heteroscedasticity in the Gaussian component of consumption growth: σ_{ci} depends on the Markov state i.[23]

6.3 Dividends of Individual Firms in the Financial Sector

In state $i \in \{1, 2, \ldots, I\}$, the dividend process of an individual financial firm is given by:

$$\Delta d_{t+1} = \mu_d + \phi_d \sigma_{ci} \eta_{t+1} + \sigma_{di} \epsilon_{t+1}, \quad \text{if no disaster} \tag{6}$$

$$\Delta d_{t+1} = \mu_d + \phi_d \sigma_{ci} \eta_{t+1} + \sigma_{di} \epsilon_{t+1} - J^d_{t+1} - \lambda_d J^a_{t+1}, \quad \text{if disaster} \tag{7}$$

where ϵ_{t+1} is standard normal and i.i.d. across time. It is the sum of an idiosyncratic and an aggregate component, which we introduce below. The term $\exp\left(-J^d_{t+1} - \lambda_d J^a_{t+1}\right)$ can be thought of as the recovery rate in case of a disaster event. The loss rate varies across financial firms. It has an idiosyncratic component J^d and a common component J^a. The parameter λ_d governs the exposure of the financial firm to aggregate tail risk. The cross-sectional mean of λ_d is 1. The idiosyncratic jump component is a Poisson mixture of normals that are i.i.d. across time and financial firms, but with common parameters $(\omega, \theta_d, \delta_d)$. We set $\theta_d = 0$, which implies that the idiosyncratic jump is truly idiosyncratic; during a disaster the average jump in any stock's log dividend growth is equal to the common component $-\lambda_d E[J^a]$.

6.4 Collective Bailout Option

The key feature of the model is the presence of the collective government guarantee, which we model as a ceiling $\underline{J}$ on the common component of the loss rate of the financial sector. The common component of the loss rate becomes the minimum of the maximum tolerated sectorwide loss rate $\underline{J}$ and the actual realized aggregate loss rate J^r:

$$J^a_{t+1} = \min(J^r_{t+1}, \underline{J}) \tag{8}$$

We model J^r as a Poisson mixture of normals with parameters $(\omega, \theta_r, \delta_r)$. For simplicity, we assume that the jump intensity is perfectly correlated among the three jump processes (J^c, J^i, J^r), but the jump

[23] Note that when J^c is activated, we have already conditioned on occurrence of a disaster. Therefore, the parameter ω is not the disaster frequency but rather the mean of the number of jumps, conditional on a disaster. There is a non-zero probability $e^{-\omega}$ of zero jumps in the disaster state. In what follows we normalize ω to 1.

size distributions are independent. We can think of the no-bailout case as $\underline{J} \to +\infty$, so that $J^a = J^r$.

6.5 Valuing the Market and Equity

We start by valuing the consumption claim. Consider the investor's Euler equation for the consumption claim $E_t[M_{t+1}R^a_{t+1}] = 1$. This can be decomposed as:

$$1 = (1-p_t)E_t[\exp(\alpha \log\beta - \frac{\alpha}{\psi}\Delta c^{ND}_{t+1} + \alpha r^{ND}_{a,t+1})] + p_t E_t[\exp(\alpha \log\beta - \frac{\alpha}{\psi}\Delta c^{D}_{t+1} + \alpha r^{D}_{a,t+1})], \quad (9)$$

where ND (D) denotes the Gaussian (disaster) component of consumption growth, dividend growth, or returns. We define "resilience" for the consumption claim as:

$$H^c_t = 1 + p_t\left(E_t\left[\exp\left\{(\gamma-1)J^c_{t+1}\right\}\right] - 1\right). \quad (10)$$

The Euler equation simplifies to:

$$1 = H^d_t E_t\left[\exp\left\{\alpha\log\beta - \frac{\alpha}{\psi}\Delta c^{ND}_{t+1} + (\alpha-1)r^{ND}_{a,t+1} + r^{ND}_{d,t+1}\right\}\right]. \quad (11)$$

We define the log resilience as:

$$h^c_t \equiv \log(H^c_t) = \log\left(1 + p_t\left[\exp\left\{\bar{h}^c\right\} - 1\right]\right), \quad (12)$$

$$\bar{h}^c \equiv \log E_t\left[\exp\left\{(\gamma-1)J^c_{t+1}\right\}\right] = \omega\left(\exp\left\{(\gamma-1)\theta_c + 0.5(\gamma-1)^2\delta^2_c\right\} - 1\right), \quad (13)$$

where we used the cumulant-generating function to compute $\bar{h}^c$. It is now clear that resilience varies only with the probability of a disaster p_t. The investor's Euler equation for the stock is $E_t[M_{t+1}R^d_{t+1}] = 1$, which can be decomposed as:

$$1 = (1-p_t)E_t\left[\exp(\alpha\log\beta - \frac{\alpha}{\psi}\Delta c^{ND}_{t+1} + (\alpha-1)r^{ND}_{a,t+1} + r^{ND}_{d,t+1})\right] \quad (14)$$

$$+p_t E_t\left[\exp(\alpha\log\beta - \frac{\alpha}{\psi}\Delta c^{D}_{t+1} + (\alpha-1)r^{D}_{a,t+1} + r^{D}_{d,t+1}).\right] \quad (15)$$

If we define "resilience" for the dividend claim as:

$$H_t^d = 1 + p_t\left(E_t\left[\exp\left\{\gamma J_{t+1}^c - J_{t+1}^d - \lambda_d J_{t+1}^a\right\}\right] - 1\right), \tag{16}$$

then the Euler equation simplifies to:

$$1 = H_t^d E_t\left[\exp\left\{\alpha\log\beta - \frac{\alpha}{\psi}\Delta c_{t+1}^{ND} + (\alpha-1)r_{a,t+1}^{ND} + r_{d,t+1}^{ND}\right\}\right]. \tag{17}$$

The log resilience of the stock is defined as before, but is determined by the bailout:

$$h_t^d \equiv \log\left[1 + p_t\left(\exp\left\{\bar{h}_d\right\} - 1\right)\right], \tag{18}$$

$$\bar{h}_d \equiv \log E_t\left[\exp\left\{\gamma J_{t+1}^c - J_{t+1}^d - \lambda_d J_{t+1}^a\right\}\right]. \tag{19}$$

The dynamics of h_t^d are fully determined by the dynamics of p_t, which follows a Markov chain. Denote by h_i^d the resilience in Markov state i. By using the independence of the three jump processes conditional on a given number of jumps, we can simplify the last term to:

$$\bar{h}_d = \log\left(\sum_{n=0}^{\infty}\frac{e^{-\omega}\omega^n}{n!}e^{n(\gamma\theta_c+0.5\gamma^2\delta_c^2)}e^{n(-\theta_d+0.5\delta_d^2)}\right. \tag{20}$$

$$\left.\times\left\{e^{n(-\lambda_d\theta_r+0.5\lambda_d^2\delta_r^2)}\Phi\left(\frac{\underline{J} - n\theta_r + n\lambda_d\delta_r^2}{\sqrt{n}\delta_r}\right) + e^{-\lambda_d\underline{J}}\Phi\left(\frac{n\theta_r - \underline{J}}{\sqrt{n}\delta_r}\right)\right\}\right). \tag{21}$$

The derivation uses proposition 1 below. The last expression, while somewhat complicated, is straightforward to compute. In the no-bailout case ($\underline{J} \to +\infty$), the last exponential term reduces to $e^{n(-\lambda_d\theta_r+0.5\lambda_d^2\delta_r^2)}$. Hence, in the no-bailout case, the resilience is given by:

$$\bar{h}^d = \omega\left(\exp\left\{\gamma\theta_c - \theta_d - \lambda_d\theta_r + 0.5(\gamma^2\delta_c^2 + \delta_\theta^2 + \lambda_d^2\delta_r^2)\right\} - 1\right)$$

An increase in bailout protection always makes the stock more resilient.

Proposition 1. *Consider two stocks i and j with the same exposures to the Gaussian risk factors. The expected return spread in a non-disaster sample is given by the differences in the resilience of these two securities:*

$$E_t[r_{t+1}^{ND,i}] + (1/2)var_t[r_{t+1}^{i,ND}] - E_t[r_{t+1}^{j,ND}] - (1/2)var_t[r_{t+1}^{i,ND}] = h_t^{d,j} - h_t^{d,i}.$$

The proof is in Appendix A. All else equal, an increase in the bailout (smaller $\underline{J}$) tends to increase the resilience of the stock and reduce the expected return in a non-disaster sample. In particular, a large financial firm stock that benefits from a bailout has negative risk-adjusted returns when benchmarked against small financial firm stocks that do not benefit directly from the bailout. To see why, fix the Gaussian and tail risk exposures $(\omega_d, \theta_d, \delta_d; \omega_r, \theta_r, \delta_r, \lambda)$ for stocks i and j. If j benefits from a bailout but i does not, then $h_t^{d,j} - h_t^{d,i} > 0$, and hence i will earn higher risk-adjusted returns in a normal sample. Any variables that affect the likelihood of a bailout will in turn impact expected excess returns net of standard risk through its effect on resilience.

An increase in the probability of a disaster reduces the dividend yield on the stock with the greatest resilience by less. This prediction of the model is confirmed in the data.

Proposition 2. *Consider two stocks i and j with the same exposures to the Gaussian risk factors. When the Markov states are highly persistent, the spread in dividend yields is given approximately by:*

$$pdi_t - pd_t^j \approx \frac{h_t^{d,i}}{1-\kappa_1^{d,i}} - \frac{h_t^{d,j}}{1-\kappa_1^{d,j}}$$

where $\kappa_1^d = \frac{e^{\overline{pd}}}{1+e^{\overline{pd}}}$.

The proof is in Appendix A. Recall that the dynamics in h_t^d are completely driven by the probability of a rare event. The model implies that the spread in dividend yields between large and small financial firm stocks has predictive power for large drops in the stock market and GDP.[24]

7 Conclusion

There is an active debate about forcing banks to carry more equity capital as a buffer against large adverse shocks to the financial system. If markets are efficient, then bank equity is not an expensive source of funding, and imposing higher capital requirements does not reduce bank value. Our international evidence does not support the notion that leverage-constrained investors inflate the share prices of large bank stocks. Instead, we find evidence that equity has always been a cheap source of funding for the largest banks in a country. In developed countries, only the largest banks' stock earns negative risk-adjusted returns, but

[24]In Section A.3 of the Appendix, we solve for the equilibrium price of individual and index stock returns. The appendix derives the equity risk premium. Absent the bailout guarantee, the disaster risk premium would be $\gamma\lambda_d p_i(2-p_i)\theta_c\theta_r$, which is always higher than the equity premium in the presence of a guarantee. Thus, the government guarantee reduces the cost of capital to financial firms.

in emerging market countries, other large nonbank financial firms do. The large-minus-small, financial-minus-non-financial, risk-adjusted spread varies across countries in ways that are consistent with the idea that stock investors price in the implicit government guarantees that protect shareholders of the largest banks in developed countries.

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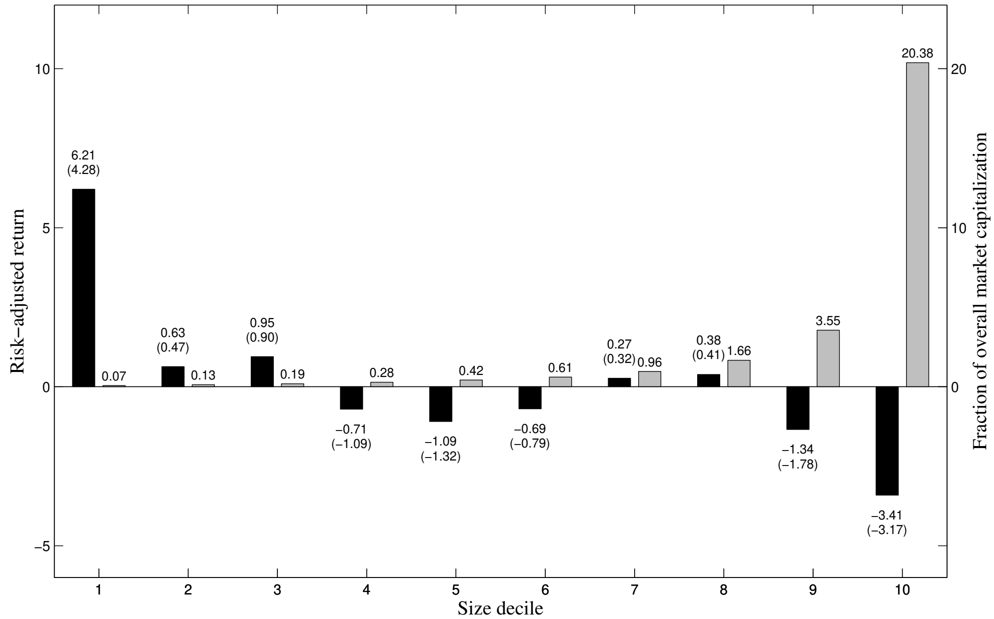

Figure 1. Risk-adjusted returns for size-sorted portfolios of financial firms vs. non-financial firms for all deciles.

This figure displays the average annualized risk-adjusted returns of all 10 size-sorted portfolios of financial versus non-financial firms by country (black bars, in percentage, left-Y axis), together with the fraction of overall market capitalization accounted for by each decile of financial firms (grey bars, in percentage, right-Y axis). In each month, for each country, we sort financial firms and non-financial firms, separately, into 10 portfolios by market capitalization. We regress excess returns of the decile portfolios on the Fama and French (1993) risk factors. Figures in parentheses are t-statistics. For each country, the longest available sample ending December 31, 2013 is selected.

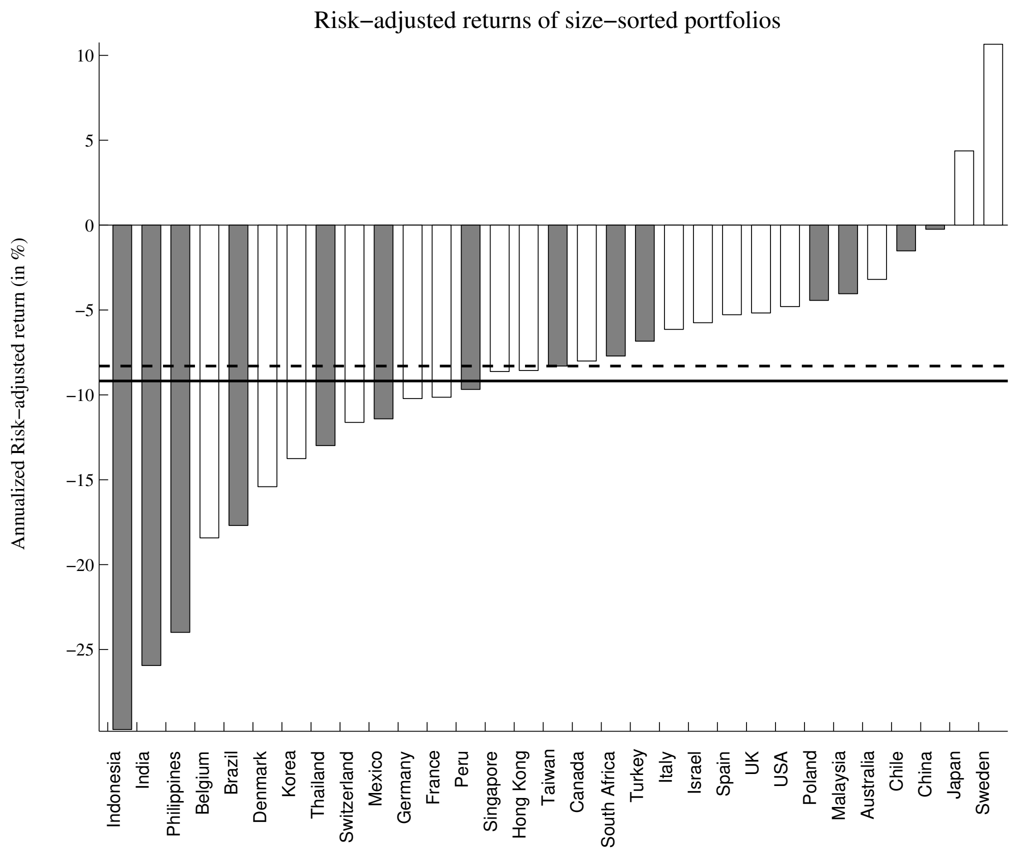

Figure 2. Risk-adjusted returns for size-sorted portfolios of financial firms vs non-financial firms

This figure presents the risk-adjusted returns of size-sorted portfolios of financial firms vs non-financial firms by country. In each month, for each country, we sort financial firms and non-financial firms, separately, into 10 portfolios by market capitalization. All returns are denominated in local currency for each country. The black solid line presents the cross-sectional average risk-adjusted return and the red dashed line presents the cross-sectional median risk-adjusted return for the LMS portfolio. For each country, the longest available sample ending December 31, 2013 is selected.

Table 1. Summary statistics.

Notes: Panel A presents summary statistics for the financial firms in our sample, by country. We report the number of distinct financial firms (N); the percentage of all publicly listed firms classified as financial firms ($\%N$), and the average market capitalization of financial firms as a percentage of total market capitalization of all publicly listed firms ($\%MCap$) in each country. Year indicates the starting year for the country in our sample. Panel B shows the summary statistics for size-sorted portfolios of financial firms. In each month, for each country, we sort financial firms into 10 portfolios by market capitalization. Large and small denote the portfolios of firms with the highest and lowest market capitalization, respectively. LMS denotes the monthly return of large minus small. We report the number of distinct financial firms (N); the average market capitalization as a percentage of the market capitalization of the entire financial intermediary sector ($\%FCap$); the turnover rate – computed as the probability (in %) that a firm migrates to another portfolio in the subsequent month ($\%Turn$); the average value-weighted monthly return (*Ret*); and its t-statistic based on standard errors clustered by time and country. All returns are denominated in local currency. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively. For each country, the longest available sample ending December 31, 2013 is selected.

Panel A: By country

Country	Classification	$Year$	N	$\%N$	$\%MCap$
Australia	developed	1991	332	12.26	24.99
Belgium	developed	1995	82	29.30	35.75
Brazil	emerging	1998	101	15.98	14.78
Canada	developed	1989	472	12.81	36.45
Chile	emerging	1997	67	23.05	32.10
China	emerging	1995	180	13.39	22.07
Denmark	developed	1989	104	30.34	22.15
France	developed	1990	218	14.88	15.60
Germany	developed	1989	476	26.23	28.85
Hong Kong	developed	1987	294	33.85	49.39
India	emerging	1991	778	10.26	9.35
Indonesia	emerging	1995	174	26.63	25.00
Israel	developed	1987	252	34.96	36.66
Italy	developed	1987	135	32.41	44.40
Japan	developed	1980	481	8.75	19.27
Malaysia	emerging	1987	188	17.61	19.45
Mexico	emerging	1994	71	20.59	11.91
Peru	emerging	2005	55	28.13	40.16
Philippines	emerging	1992	122	31.23	27.56
Poland	emerging	2009	146	15.96	39.42
Singapore	developed	1987	116	25.88	41.72
South Africa	emerging	1991	180	16.30	22.11
South Korea	developed	1985	248	16.52	20.78
Spain	developed	1999	79	33.09	40.81
Sweden	developed	1995	109	19.01	26.88
Switzerland	developed	1990	111	29.08	32.79
Taiwan	emerging	1997	124	9.93	24.52
Thailand	emerging	1989	174	26.35	34.05
Turkey	emerging	2001	81	14.63	31.29
UK	developed	1980	778	14.04	17.85
USA	developed	1980	3,201	21.00	13.16

Panel B: By size-sorted portfolio

	small				large				LMS		
	N	$\%FCap$	$\%Turn$	*Ret*	N	$\%FCap$	$\%Turn$	*Ret*	*Ret*		*t-stat*
All countries	143	0.28	12.65	20.06	46	72.54	2.84	12.22	−7.84	***	−2.98
Developed markets	197	0.20	11.55	14.60	57	76.01	2.33	10.87	−3.74	***	3.11
Emerging markets	77	0.42	16.17	29.29	32	66.59	3.94	14.52	−14.77	***	−4.32

Table 2. Risk-adjusted returns for size-sorted portfolios of financial firms and non-financial firms.

Notes: This table presents estimates from pooled OLS regression of monthly excess returns of size-sorted portfolios on equity risk factors. All returns and risk factors are expressed in local currency. In each month, for each country, we sort financial firms and non-financial firms separately into 10 size-sorted portfolios by market capitalization. Large and small denote the portfolios of firms with the highest and lowest market capitalization, respectively. We regress excess returns to large, small, and their difference, denoted LMS, using Fama and French (1993) risk factors. The table displays the estimates for risk-adjusted return (α) and its t-statistic based on standard errors clustered by time and country. Columns titled `Fin` refer to financial firms, columns titled `Non-fin` refer to non-financial firms, and columns titled `Fin Minus Non-fin` refer to their difference. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Coefficients are annualized, multiplied by 100, and expressed in percentages. For each country, the longest available sample ending December 31, 2013 is selected.

	`Fin`		`Non-fin`		`Fin Minus Non-Fin`	
	α	*t-stat*	α	*t-stat*	α	*t-stat*
Panel A: All countries						
Large	-2.41**	-2.41	1.46***	2.89	-3.86***	-3.50
Small	8.07***	3.75	3.98***	3.01	4.09***	2.93
LMS	-10.47***	-4.50	-2.52*	-1.72	-7.96***	-4.73
Panel B: Developed markets						
Large	-3.40***	-3.01	0.91*	1.68	-4.31***	-3.11
Small	6.07***	2.65	4.12**	2.34	1.95*	1.79
LMS	-9.47***	-3.83	-3.21*	-1.69	-6.26***	-3.54
Panel C: Emerging markets						
Large	-1.51	-1.04	2.19***	2.94	-3.70**	-2.44
Small	12.31***	3.18	3.81***	2.02	8.51***	3.23
LMS	-13.82***	-3.26	-1.62***	-0.76	-12.21***	-4.25

Table 3. Risk-adjusted returns for size-sorted portfolio of largest financial firms by type.

Notes: This table presents the estimates from the pooled OLS regression of monthly excess returns of size-sorted portfolios of financial firms on standard stock risk factors for data. All returns and risk factors expressed in local currency. In each month, for each country, we sort financial firms into 10 size-sorted portfolios by market capitalization. Large denotes the portfolio of firms with the highest market capitalization. We regress excess returns to large on the Fama and French (1993) risk factors. The table displays the estimates for the risk-adjusted return (α) and its t-statistic based on standard errors clustered by time and country. The first two columns report the results for the longest available sample for each country, the next two columns report the results over 1990-2013, and the last two columns report the results over 2000-2013. The large portfolio is split into Banks & Financial Services, Insurance, and RE Investment firms. Results are reported when pooling across countries (Panel A), across developed markets only (Panel B), and across emerging markets only (Panel C). Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Coefficients are annualized, multiplied by 100, and expressed in percentages. For each country, the longest available sample ending December 31, 2013 is selected.

	Full Sample		1990-2013		2000-2013	
	α	*t-stat*	α	*t-stat*	α	*t-stat*
			Panel A: All countries			
Banks & Fin Services	-2.01*	-1.80	-2.17**	-1.83	-3.16**	-2.08
Insurance	-0.29	-0.25	-0.32	-0.27	-1.44	-1.06
RE Investment	-2.28***	-3.42	-2.11***	-3.01	-2.07*	-1.66
			Panel B: Developed markets			
Banks & Fin Services	-3.29**	-2.28	-3.78**	-2.44	-6.40***	-3.48
Insurance	-0.21	-0.18	-0.30	-0.24	-1.35	-0.76
RE Investment	-1.87*	-1.67	-1.60	-1.41	-1.30	-0.98
			Panel C: Emerging markets			
Banks & Fin Services	-0.64	-0.47	-0.50	-0.37	0.20	0.13
Insurance	-2.06	-1.02	-1.93	-0.97	-1.93	-1.55
RE Investment	-3.72***	-4.71	-3.64***	-4.45	-3.72	-1.56

Table 4. Forecasting regressions for the aggregate stock market and gross domestic product.

Notes: This table presents the estimates from a pooled conditional fixed-effect Logit regression. The dependent variable is a dummy variable that takes a value of 1 when the country H-month ahead growth rate of gross domestic product (for Panel A) or the H-month ahead return on the aggregate stock market index (for Panel B) is below its 10^{th}-percentile, with $H = \{3, 6, 9, 12\}$. In each month, for each country, we sort financial firms into 10 size-sorted portfolios by market capitalization. Large and small denote the portfolios of firms with the highest and lowest market capitalization, respectively. The independent variable is the monthly value-weighted dividend yield of large over small financial firms, denoted by DY_{LMS}. In each panel, the first row reports the loading on the DY_{LMS} portfolio, and the second row reports its corresponding t-statistic. The last row indicates the change in the odds of a drop in the H-period ahead return of the aggregate stock index or gross domestic product growth rates below its 10^{th}-percentile for a 1-standard deviation increase in the monthly return to LMS. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively. For each country, the longest available sample ending December 31, 2013 is selected.

	Horizon (H) in months			
	3	6	9	12
	Panel A: Gross domestic product			
DY_{LMS}	-2.73**	-2.44*	-2.51*	-1.30
t-stat	-2.27	-1.90	-1.91	-0.90
Δ *Odds* (%)	12.43	11.04	11.38	5.75
	Panel B: Aggregate stock market			
DY_{LMS}	-2.02***	-0.57	-0.06	-0.55
t-stat	-2.97	-0.76	-0.07	-0.73
Δ *Odds* (%)	9.12	2.49	0.24	2.42

Table 5. Performance of the LMS portfolio for financial firms during economic crisis.

Notes: This table shows the value of $100 invested in a portfolio that goes long in large financial firms and short in small financial firms during economic crisis. In each country, an economic crisis is defined as quarters in which the GDP is below the $10^{th}-$percentile level for that country. In each month, for each country, we sort financial firms and non-financial firms separately into 10 size-sorted portfolios by market capitalization. Large and small refer to firms with the highest and lowest market capitalization, respectively. LMS is the monthly excess return of large over small firms. In each country, $100 is invested in this portfolio at the start of the crisis. The column labeled `Value` represents the risk-adjusted return on this portfolio at the end of the crisis. The columns labeled `Delistings` represents the average number of financial firms classified as small at the start of the crisis that delist per month during the crisis in excess of the number of firms that are in the large portfolio at the start of the crisis that delist per month during the crisis. The number of delisted firms is expressed as a percentage of firms in the small and large portfolio at the start of the crisis, respectively.

	`Value`	`Crisis delistings`		
Country		small	large	LMS
Panel A: Country-level				
Australia	128.36	2.38	2.22	-0.16
Belgium	81.42	2.22	0.00	-2.22
Brazil	96.99	0.00	0.00	0.00
Canada	80.46	0.62	0.00	-0.62
Chile	123.12	0.00	0.00	0.00
China	111.95	0.00	0.00	0.00
Denmark	136.95	0.95	0.00	-0.95
France	167.22	1.11	0.38	-0.73
Germany	104.78	0.41	1.79	1.38
Hong Kong	99.13	0.00	0.00	0.00
India	85.84	0.00	0.00	0.00
Indonesia	67.41	2.22	0.00	-2.22
Israel	89.98	0.00	0.00	0.00
Italy	91.60	0.00	0.00	0.00
Japan	106.01	0.37	0.13	-0.24
Malaysia	69.54	0.00	0.00	0.00
Mexico	110.70	0.00	0.00	0.00
Peru	101.23	0.00	0.00	0.00
Philippines	93.91	0.00	0.00	0.00
Poland	129.56	0.37	0.21	-0.15
Singapore	80.67	1.85	0.00	-1.85
South Africa	169.96	0.00	0.00	0.00
South Korea	69.82	6.06	0.00	-6.06
Spain	114.07	0.00	0.00	0.00
Sweden	169.61	0.00	0.00	0.00
Switzerland	118.87	0.00	0.00	0.00
Taiwan	114.48	4.17	0.00	-4.17
Thailand	80.50	1.18	0.49	-0.69
Turkey	45.26	0.00	0.00	0.00
UK	138.87	2.05	0.86	-1.19
USA	107.75	0.66	0.00	-0.66
Panel B: Group averages				
All countries	106.00	0.86	0.20	-0.66
developed markets	116.19	0.90	0.38	-0.52
emerging markets	97.61	0.82	0.04	-0.78

Table 6. Legal environment and the size anomaly for financial firms.

Notes: This table reports the results for a panel regression of the risk-adjusted return to the LMS portfolio of financial firms on variables capturing a country's legal environment. In each month, for each country, we sort financial firms and non-financial firms separately into 10 size-sorted portfolios by market capitalization. Large and small denote portfolios of firms with the highest and lowest market capitalization, respectively. We regress the difference in the return to large minus small, denoted LMS, on the Fama and French (1993) risk factors over 2-year non-overlapping windows. The dependent variable is the estimated risk-adjusted return on LMS for country j. The regressors are: a dummy variable that equals 1 if country j follows UK law (L_{UK}); a dummy variable that equals 1 if country j follows French law (L_{FR}); a dummy variable that equals 1 if country j follows German law (L_{GR}); a dummy variable that equals 1 if country j follows Scandinavian law (L_{SC}); an index measuring property rights in a country (*Property*); an index measuring how left-leaning the Federal government is in a country ($Left$); and an index measuring the perception of integrity of the government in a country ($Integrity$). Data for legal systems come from La Porta, Lopez-de Silanes, Shleifer, and Vishny (2000); for $Property$ and $Integrity$ from the Heritage foundation; for $Left$ from the World Statesman (`http:\www.worldstatesman.com`). Each column reports the results for a separate panel regression specification. In parentheses, we report robust t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels, respectively. For each country, the longest available sample ending December 31, 2013 is selected. The regressors are standardized to mean zero and variance one. TFE denotes time fixed effects.

Variable	L_{UK}	L_{FR}	L_{GR}	L_{SC}	$Property$	$Left$	$Integrity$
Fin	-3.71***	0.85	1.43	3.33***	2.14*	-1.27	4.09***
	(-3.21)	(0.78)	(1.57)	(3.89)	(1.78)	(-1.11)	(3.29)
N	355	355	355	355	286	355	286
R^2(%)	12.15	9.44	9.72	11.66	8.32	9.61	11.08
Non-fin	-3.62***	3.69***	-0.74	1.30***	-0.48	0.69	-0.30
	(-6.19)	(6.79)	(-1.09)	(3.45)	(-0.69)	(1.21)	(-0.44)
N	446	446	446	446	307	446	307
R^2(%)	19.11	19.35	12.12	12.76	3.58	12.09	3.47
TFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Business environment and the size anomaly for financial firms.

Notes: This table shows the results for the panel regression of the risk-adjusted return to the LMS portfolio of financial firms on variables capturing a country's business environment. In each month, for each country, we sort financial firms and non-financial firms separately into 10 size-sorted portfolios by market capitalization. Large and small denote portfolios of firms with the highest and lowest market capitalization, respectively. We regress the difference in the return to large minus small, denoted LMS, on the Fama and French (1993) risk factors over 2-year non-overlapping windows. The dependent variable is the estimated risk-adjusted return on LMS for country j. The regressors are: an index that measures the strength of corporate disclosure (*Disclose*); an index that measures the strength of corporate governance (*Govern*); the number of publicly-listed firms in the country as a percentage of market capitalization in USD ($Nfirm$); an index that measures the ability of the government to formulate and implement sound business regulations (*Regln*); the strength of bankruptcy resolution measured by looking at average recovery rates, time taken to resolve bankruptcy cases, outcomes, and cost of bankruptcy in a country (*Bankrupt*); an index that measures the extent of economic and political globalization (*Global*); the overall market capitalization of all publicly-listed firms in the country as a percentage of GDP ($Mktcap$); an index that measures the risk of appropriation by the government (*ExpropRisk*); the average annual volatility of the primary stock market index ($StockVol$); and the average annual return on an index of all publicly-traded firms in the country (*StockRet*). Data is from La Porta, Lopez-de Silanes, Shleifer, and Vishny (2000), Global Economic data (`http:\www.globaleconomy.com`), and Doing Business Database – World Bank (`http:\www.doingbusiness.org`). Each column reports the results for a separate panel regression specification. In parentheses, we report robust t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels, respectively. For each country, the longest available sample ending December 31, 2013 is selected. The regressors are standardized to mean zero and variance one. TFE and CFE denote time and country fixed effects, respectively.

Variable	*Disclose*	*Govern*	$Nfirm$	*Regln*	*Bankrupt*	*Global*	$Mktcap$	*ExpropRisk*	$StockVol$	*StockRet*
Fin	2.84**	3.10***	-0.90	4.27***	-17.69***	15.01**	-1.66	-5.30***	-4.10**	0.40
	(2.35)	(2.76)	(-0.44)	(3.12)	(-2.75)	(2.58)	(-2.09)	(-0.75)	(-2.06)	(0.22)
N	332	332	315	265	153	332	316	355	322	327
$R^2(\%)$	10.12	10.44	32.03	10.10	59.74	37.77	31.93	15.15	37.66	36.64
Non-fin	-1.22**	-0.63	-0.05	0.34	-4.52	-2.94	-1.04	0.93	0.53	1.26*
	(-2.13)	(-1.21)	(-0.08)	(0.49)	(-1.09)	(-0.65)	(-0.91)	(1.19)	(0.54)	(1.93)
N	412	412	388	279	155	417	390	446	372	378
$R^2(\%)$	15.30	14.55	51.34	3.21	69.20	42.90	51.39	12.28	49.40	48.10
TFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CFE	No	No	Yes	No	Yes	Yes	Yes	No	Yes	Yes

Table 8. Financial environment and the size anomaly for financial firms.

Notes: This table reports the results for the panel regression of the risk-adjusted return to the LMS portfolio of financial firms on variables capturing a country's financial environment. In each month, for each country, we sort financial firms and non-financial firms separately into 10 size-sorted portfolios by market capitalization. Large and small denote portfolios of firms with the highest and lowest market capitalization, respectively. We regress the difference in the return to large minus small, denoted LMS, on the Fama and French (1993) risk factors over 2-year non-overlapping windows. The dependent variable is the estimated risk-adjusted return on LMS for country j. The regressors are: branch network size per 100,00 inhabitants ($Branches$); demand deposits-to-GDP ($Deposits$); non-performing loans-to-total loans ($Nonperform$); financial firm liquid assets-to-total assets ($Liquidity$); financial firm profits-to-equity ($Profit$); defaulted loans-to-total loans ($Defaults$); financial firm capital-to-assets ($Leverage$); total volume of bond markets ($BondDepth$); financial claims held by non-residents ($Foreign$); a dummy that equals 1 if country has deposit insurance ($Insurance$); percentage of total financial firm assets held by 3 largest financial firms ($Top3$); percentage of total assets held by 5 largest financial firms ($Top5$); credit to private entities as a percentage of GDP ($PvtCredit$); and credit to government as a percentage of GDP ($GovCredit$). Data is from Global Economic data (http:\www.globaleconomy.com), Bankscope – Bureau van Dijk, Bank of International Settlements, Global Findex – World Bank, International Financial Statistics, and International Monetary Fund. Each column reports the results for a separate panel regression specification. In parentheses, we report robust t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels, respectively. For each country, the longest available sample ending December 31, 2013 is selected. The regressors are standardized to mean zero and variance one. TFE and CFE denote time and country fixed effects, respectively.

Variable	$Branches$	$Deposits$	$Nonperform$	$Liquidity$	$Profit$	$Defaults$	$Leverage$	$BondDepth$	$Foreign$	$Insurance$	$Top3$	$Top5$	$PvtCredit$	$GovCredit$
Fin	-11.20***	-6.35*	-6.47***	3.31***	4.50***	-7.44***	-0.54	2.97	3.18***	1.45	-4.06*	-8.32***	0.54	-0.73
	(-3.02)	(-1.83)	(-3.63)	(2.99)	(3.41)	(-4.46)	(-0.17)	(1.01)	(3.42)	(1.21)	(-1.91)	(-3.10)	(0.28)	(-0.39)
N	144	320	243	256	256	230	228	292	297	355	253	245	340	341
R^2(%)	63.15	35.79	47.89	8.67	43.92	50.44	44.04	38.90	10.95	9.71	44.05	47.4	35.64	35.62
Non-fin	1.69	-1.52	0.17	3.61***	0.29	0.04	-0.09	-0.36	0.51	-0.41	-1.00	-1.56	1.29	2.22**
	(1.28)	(-0.80)	(0.23)	(5.33)	(0.55)	(0.05)	(-0.09)	(-0.31)	(0.87)	(-0.14)	(-1.28)	(-1.85)	(1.27)	(2.05)
N	146	403	257	270	270	239	237	324	342	310	267	259	425	404
R^2(%)	68.20	43.30	63.20	13.04	63.00	63.20	63.20	59.70	13.86	0.11	63.70	63.40	41.90	44.70
TFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CFE	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes

Table 9. Sovereign environment and the size anomaly for financial firms.

Notes: This table reports the results for the panel regression of the risk-adjusted return to the LMS portfolio of financial firms on variables capturing a country's sovereign environment. In each month, for each country, we sort financial firms and non-financial firms separately into 10 size-sorted portfolios by market capitalization. Large and small denote portfolios of firms with the highest and lowest market capitalization, respectively. We regress the difference in the return to large minus small, denoted LMS, on the Fama and French (1993) risk factors over 2-year non-overlapping windows. The dependent variable is the estimated risk-adjusted return on LMS for country j. The regressors are: the fiscal surplus (as a percentage of GDP) in the country ($Surplus$); the difference in the yield-to-maturity on the long-term bond issued by a country and the yield-to-maturity on the long-term bond issued by the U.S. Treasury ($Spread$); the ratio of central bank assets to GDP ($CentBank$); the value of the index of inflation at year end ($Inflation$); and the per-capita GDP (GDP) in the country. Data is from Global Economic data (`http:\www.globaleconomy.com`), International Financial Statistics, International Monetary Fund, and World Development Indicators – World Bank. Each column reports the results for a separate panel regression specification. In parentheses, we report robust t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels, respectively. For each country, the longest available sample ending December 31, 2013 is selected. The regressors are standardized to mean zero and variance one. TFE and CFE denote time and country fixed effects, respectively.

Variable	$Surplus$	$Spread$	$CentBank$	$Inflation$	GDP
Fin	-0.92	4.17*	-3.91**	5.05**	-25.60***
	(-0.48)	(1.86)	(-2.25)	(2.24)	(-3.13)
N	281	324	307	341	346
R^2(%)	35.59	27.86	36.96	37.73	38.13
Non-fin	-0.77	0.97	0.32	-4.61**	6.93*
	(-1.01)	(1.28)	(0.33)	(-2.31)	(1.75)
N	281	387	390	425	434
R^2(%)	60.86	39.14	44.50	45.50	43.30
TFE	Yes	Yes	Yes	Yes	Yes
CFE	Yes	No	Yes	Yes	Yes

Table 10. Regulatory environment and the size anomaly for financial firms.

Notes: This table reports the results for the panel regression of the risk-adjusted return to the LMS portfolio of financial firms on variables capturing a country's sovereign environment. In each month, for each country, we sort financial firms and non-financial firms separately into 10 size-sorted portfolios by market capitalization. Large and small denote portfolios of firms with the highest and lowest market capitalization, respectively. We regress the difference in the return to large minus small, denoted LMS, on the Fama and French (1993) risk factors over 2-year non-overlapping windows, $t+1$ to $t+2$. The dependent variable is the estimated risk-adjusted return on LMS for country j. The regressors are: the cost of each financial crisis as a percentage of GDP ($Cost$); the amount of liquidity support provided to financial firms as a percentage of GDP ($LiqSupport$); the level of non-performing loans ($NPLevels$); the increase in sovereign debt to support financial firms ($SovDebtInc$); a dummy variable that equals 1 if monetary expansion was undertaken in response to crisis ($MonetaryExp$); a dummy variable that equals 1 if entry restrictions were placed on the financial sector ($EntryBarrier$); a dummy that equals 1 if financial supervision was tightened ($Supervision$); the number of private and public (i.e. non-government owned) financial firms ($Privatize$); a dummy variable that equals 1 if reforms were enacted ($Reform$) and if restrictions were placed on financial firms ($Restrict$) after each financial crisis. Data is from Laeven and Valencia (2008). Each column reports the results for a separate panel regression specification. In parentheses, we report robust t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels, respectively. For each country, the longest available sample ending December 31, 2013 is selected. The regressors are standardized to mean zero and variance one. TFE and CFE denote time and country fixed effects, respectively.

Variable	$Cost$	$LiqSupport$	$NPLevel$	$SovDebtInc$	$MonetaryExp$	$EntryBarrier$	$Supervision$	$Privatize$	$Reform$	$Restrict$
Fin	-4.52***	-2.75**	-3.89***	-4.24***	-3.33***	-1.88	5.35**	7.04***	5.64*	0.41
	(-3.70)	(-2.42)	(-2.69)	(-3.43)	(-2.68)	(-0.76)	(2.11)	(2.81)	(1.78)	(0.27)
N	355	355	355	355	355	355	355	355	355	355
$R^2(\%)$	38.94	36.95	38.00	38.58	37.35	35.77	36.68	38.08	36.30	35.71
Non-fin	0.11	2.70	1.20	-0.16	1.63***	0.55	-2.29	0.74	1.04	-0.48
	(0.16)	(1.32)	(0.91)	(-0.19)	(3.86)	(0.38)	(1.14)	(0.65)	(0.67)	(-0.84)
N	446	446	446	446	446	446	446	446	446	446
$R^2(\%)$	42.60	46.00	43.20	42.60	43.70	42.70	43.20	42.70	42.70	42.70
TFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix
Equity is Cheap for Large Financial Institutions

A Model

Proof of Proposition 1: We start from the Euler equation in equation 17.

$$0 = h_t^d + \log E_t \left[\exp \left\{ \alpha \log \beta - \frac{\alpha}{\psi} \Delta c_{t+1}^{ND} + (\alpha - 1) r_{a,t+1}^{ND} + r_{d,t+1}^{ND} \right\} \right]. \tag{22}$$

Using log-normality, this in turn implies that the expected return in a non-disaster sample is given by:

$$E_t[r_{t+1}^{i,ND}] + (1/2) var_t[r_{t+1}^{i,ND}] - r^f = +\frac{\alpha}{\psi} cov_t(\Delta c_{t+1}^{ND}, r_{d,t+1}^{i,ND}) - (\alpha - 1) cov(r_{a,t+1}^{ND}, r_{d,t+1}^{i,ND}) - h_t^{d,i}.$$

The result immediately follows.

Proof of proposition 2: Solving the Euler equation for the dividend claim amounts to solving for the log price-dividend ratio in each state i, pd_i. We can solve a system of N equations for pd_i:

$$\begin{aligned} pd_i \quad &= \quad h_i^d + \alpha \log \beta - \gamma \mu_c + (\alpha - 1)\left(\kappa_0^c - \kappa_1^c wc_i\right) + \kappa_0^d + \mu_d + \frac{1}{2}(\phi_d - \gamma)^2 \sigma_{ci}^2 + \frac{1}{2}\sigma_{di}^2 && (23) \\ & \quad + \log \left(\sum_{j=1}^{N} \pi_{ij} \exp \left\{ (\alpha - 1) wc_j + \kappa_1^d pd_j \right\} \right), && (24) \end{aligned}$$

together with the linearization constants in (31) and (32), and the mean pd ratio:

$$\overline{pd} \quad = \quad \sum_j \Pi_j pd_j. \tag{25}$$

Now take the limit $\pi_{ii} \to 1$. That delivers the result.

A.1 Valuing the Consumption Claim

We start by valuing the consumption claim. Consider the investor's Euler equation for the consumption claim $E_t[M_{t+1} R_{t+1}^a] = 1$. This can be decomposed as:

$$1 \quad = \quad (1 - p_t) E_t[\exp(\alpha \log \beta - \frac{\alpha}{\psi} \Delta c_{t+1}^{ND} + \alpha r_{a,t+1}^{ND})] + p_t E_t[\exp(\alpha \log \beta - \frac{\alpha}{\psi} \Delta c_{t+1}^{D} + \alpha r_{a,t+1}^{D})], \tag{26}$$

where ND (D) denotes the Gaussian (disaster) component of consumption growth, dividend growth or returns. We define "resilience" for the consumption claim as:

$$H_t^c = 1 + p_t \left(E_t \left[\exp \left\{ (\gamma - 1) J_{t+1}^c \right\} \right] - 1 \right). \tag{27}$$

We log-linearize the total wealth return $R_{t+1}^a = \frac{W_{t+1}}{W_t - C_t}$ as follows: $r_{a,t+1} = \kappa_0^c + wc_{t+1} - \kappa_1^c wc_t + \Delta c_{t+1}$ with linearization constants:

$$\begin{aligned} \kappa_1^c \quad &= \quad \frac{e^{\overline{wc}}}{e^{\overline{wc}} - 1} && (28) \\ \kappa_0^c \quad &= \quad -\log\left(e^{\overline{wc}} - 1\right) + \kappa_1^c \overline{wc}. && (29) \end{aligned}$$

The wealth-consumption ratio differs across Markov states. Let wc_i be the log wealth-consumption ratio in Markov state i. The mean log wealth-consumption ratio can be computed using the stationary distribution:

$$\overline{wc} = \sum_{i=1}^{I} \Pi_i wc_i \tag{30}$$

where Π_i is the i^{th} element of vector Π. Note that the linearization constants κ_0^c and κ_1^c depend on $\overline{wc}$. Using the log linearization for the total wealth return, the Euler equation can be restated as follows:

$$1 = \exp(h_t^c) E_t \left[\exp \left\{ \alpha \log \beta - \frac{\alpha}{\psi}(\mu_c + \sigma_{ci}\eta_{t+1}) + \alpha(\kappa_0^c + wc_{t+1} - \kappa_1^c wc_t + \Delta c_{t+1}^{ND}) \right\} \right].$$

Resilience takes a simple form in our setting:

$$\begin{aligned} h_t^c &\equiv \log(H_t^c) = \log\left(1 + p_t\left[\exp\left\{\bar{h}^c\right\} - 1\right]\right), \\ \bar{h}^c &\equiv \log E_t\left[\exp\left\{(\gamma-1)J_{t+1}^c\right\}\right] = \omega\left(\exp\left\{(\gamma-1)\theta_c + .5(\gamma-1)^2\delta_c^2\right\} - 1\right), \end{aligned}$$

where we use the cumulant-generating function to compute $\bar{h}^c$. It is now clear that resilience varies only with the probability of a disaster p_t. Therefore, it too is a Markov chain. Denote by h_i^c the log resilience in Markov state i. Solving the Euler equation for the consumption claim amounts to solving for the log wealth-consumption ratio in each state i. We obtain the system of I equations as follows, which can be solved for wc_i, $i = 1, \dots I$:

$$1 = \exp(h_i^c) \exp\left\{\alpha(\log\beta + \kappa_0^c) + (1-\gamma)\mu_c - \alpha\kappa_1^c wc_i + \frac{1}{2}(1-\gamma)^2\sigma_{ci}^2\right\} \sum_{j=1}^{N} \pi_{ij} \exp\left\{\alpha wc_j\right\}$$

where π_{ij} is the transition probability between states i and j. Taking logs on both sides we get a system of equations that can be solved in conjunction with (28), (29), and (30):

$$0 = h_i^c + \alpha(\log\beta + \kappa_0^c) + (1-\gamma)\mu_c - \alpha\kappa_1^c wc_i + \frac{1}{2}(1-\gamma)^2\sigma_{ci}^2 + \log\sum_{j=1}^{N}\pi_{ij}\exp\left\{\alpha wc_j\right\}.$$

A.2 Valuing the Dividend Claim

The investor's Euler equation for the stock is $E_t[M_{t+1}R_{t+1}^d] = 1$, which can be decomposed as:

$$\begin{aligned} 1 &= (1-p_t)E_t\left[\exp(\alpha\log\beta - \frac{\alpha}{\psi}\Delta c_{t+1}^{ND} + (\alpha-1)r_{a,t+1}^{ND} + r_{d,t+1}^{ND})\right] \\ &\quad + p_t E_t\left[\exp(\alpha\log\beta - \frac{\alpha}{\psi}\Delta c_{t+1}^{D} + (\alpha-1)r_{a,t+1}^{D} + r_{d,t+1}^{D})\right] \end{aligned}$$

If we define "resilience" for the dividend claim as:

$$H_t^d = 1 + p_t\left(E_t\left[\exp\left\{\gamma J_{t+1}^c - J_{t+1}^d - \lambda_d J_{t+1}^a\right\}\right] - 1\right),$$

then the Euler equation simplifies to:

$$1 = H_t^d E_t\left[\exp\left\{\alpha\log\beta - \frac{\alpha}{\psi}\Delta c_{t+1}^{ND} + (\alpha-1)r_{a,t+1}^{ND} + r_{d,t+1}^{ND}\right\}\right].$$

We log-linearize the stock return on bank i, R_{t+1}^d, as $r_{d,t+1} = \kappa_0^d + \kappa_1^d pd_{t+1} - pd_t + \Delta d_{t+1}$, with the linearization constants:

$$\kappa_1^d = \frac{e^{\overline{pd}}}{1+e^{\overline{pd}}}, \tag{31}$$

$$\kappa_0^d = \log(1+e^{\overline{pd}}) - \kappa_1^d\overline{pd}. \tag{32}$$

To compute the resilience term, we proceed as before:

$$\begin{aligned} h_t^d &\equiv \log\left(1 + p_t\left(\exp\left\{\bar{h}_d\right\} - 1\right)\right), \\ \bar{h}_d &\equiv \log E_t\left[\exp\left\{\gamma J_{t+1}^c - J_{t+1}^d - \lambda_d J_{t+1}^a\right\}\right]. \end{aligned}$$

By using the independence of the three jump processes conditional on a given number of jumps, we can simplify the last term to:

$$\begin{aligned}\bar{h}_d &= \log\left(\sum_{n=0}^{\infty}\frac{e^{-\omega}\omega^n}{n!}e^{n(\gamma\theta_c+.5\gamma^2\delta_c^2)}e^{n(-\theta_d+.5\delta_d^2)}\right.\\ &\quad\left.\times\left\{e^{n(-\lambda_d\theta_r+.5\lambda_d^2\delta_r^2)}\Phi\left(\frac{\underline{J}-n\theta_r+n\lambda_d\delta_r^2}{\sqrt{n}\delta_r}\right)+e^{-\lambda_d\underline{J}}\Phi\left(\frac{n\theta_r-\underline{J}}{\sqrt{n}\delta_r}\right)\right\}\right).\end{aligned}$$

The derivation uses Lemma 1 below. The last expression, while somewhat complicated, is straightforward to compute. In the no-bailout case ($\underline{J}\to+\infty$), the last exponential term reduces to $e^{n(-\lambda_d\theta_r+.5\lambda_d^2\delta_r^2)}$. The dynamics of h_t^d are fully determined by the dynamics of p_t, which follows a Markov chain. Denote by h_i^d the resilience in Markov state i.

Solving the Euler equation for the dividend claim amounts to solving for the log price-dividend ratio in each state i, pd_i. We can solve the following system of N equations for pd_i:

$$\begin{aligned}pd_i &= h_i^d+\alpha\log\beta-\gamma\mu_c+(\alpha-1)\left(\kappa_0^c-\kappa_1^c wc_i\right)+\kappa_0^d+\mu_d+\frac{1}{2}(\phi_d-\gamma)^2\sigma_{ci}^2+\frac{1}{2}\sigma_{di}^2\\ &\quad+\log\left(\sum_{j=1}^{N}\pi_{ij}\exp\left\{(\alpha-1)wc_j+\kappa_1^d pd_j\right\}\right),\end{aligned}$$

together with the linearization constants in (31) and (32), and the mean pd ratio:

$$\overline{pd} = \sum_j \Pi_j pd_j. \tag{33}$$

A.3 Dividend Growth and Return Variance, Return Covariance, and the Equity Risk Premium

Preliminaries Recall that dividend growth in state i today is

$$\begin{aligned}\Delta d_i &= (1-p_i)\Delta d_i^{ND}+p_i\Delta d_i^{D},\\ \Delta d_i^{ND} &= \mu_d+\phi_d\sigma_{ci}\eta+\sigma_{di}\epsilon,\\ \Delta d_i^{D} &= \mu_d+\phi_d\sigma_{ci}\eta+\sigma_{di}\epsilon-J^d-\lambda_d J^a\end{aligned}$$

where the shock $\epsilon=\sqrt{\xi_d}\epsilon^a+\sqrt{1-\xi_d}\epsilon^i$ is the sum of a common shock and an idiosyncratic shock, both of which are standard normally distributed and i.i.d. over time. Stock returns in state i today and assuming a transition to state j next period are:

$$\begin{aligned}r_i &= (1-p_i)r_i^{ND}+p_i r_i^{D},\\ r_i^{ND} &= \mu_{rij}+\phi_d\sigma_{ci}\eta+\sigma_{di}\epsilon,\\ r_i^{D} &= \mu_{rij}+\phi_d\sigma_{ci}\eta+\sigma_{di}\epsilon-J^d-\lambda_d J^a,\\ \mu_{rij} &= \mu_d+\kappa_0^d+\kappa_1^d pd_j-pd_i,\\ J^a &= \min(J^r,\underline{J}).\end{aligned}$$

We are interested in computing the variance of dividend growth rates, the variance of returns, and the covariance between a pair of returns. This will allow us to compute the volatility of returns and the correlation of returns.

Applying Lemma 4 below to the J^a process and conditioning on n jumps, we get that

$$\begin{aligned}E[J^a|n] &= E[\min(J^r,\underline{J})|n]\\ &= E[J^r 1_{(J^r<\underline{J})}|n]+\underline{J}E[1_{(J^r\geq\underline{J})}|n]\\ &= n\theta_r\Phi\left(\frac{\underline{J}-n\theta_r}{\sqrt{n}\delta_r}\right)-\sqrt{n}\delta_r\phi\left(\frac{\underline{J}-n\theta_r}{\sqrt{n}\delta_r}\right)+\underline{J}\Phi\left(\frac{n\theta_r-\underline{J}}{\sqrt{n}\delta_r}\right),\end{aligned}$$

and

$$\begin{aligned}E[J^{a2}|n] &= E[\min(J^r,\underline{J})^2|n]\\ &= E[J^{r2}1_{(J^r<\underline{J})}|n]+\underline{J}^2E[1_{(J^r\geq\underline{J})}|n]\\ &= \left(n\delta_r^2+n^2\theta_r^2\right)\Phi\left(\frac{\underline{J}-n\theta_r}{\sqrt{n}\delta_r}\right)-\sqrt{n}\delta_r(\underline{J}+n\theta_r)\phi\left(\frac{\underline{J}-n\theta_r}{\sqrt{n}\delta_r}\right)+\underline{J}^2\Phi\left(\frac{n\theta_r-\underline{J}}{\sqrt{n}\delta_r}\right).\end{aligned}$$

Note that the corresponding moments for the J^d process are:

$$\begin{aligned} E[J^d|n] &= n\theta_d \\ E[J^{d^2}|n] &= n\delta_d^2 + n^2\theta_d^2. \end{aligned}$$

We now average over all possible realizations of the number of jumps n to get:

$$\begin{aligned} E[J^d] &= \sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} E[J^d|n] = \theta_d, \\ E[J^{d^2}] &= \sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} E[J^{d^2}|n] = \delta_d^2 + 2\theta_d^2, \\ E[J^a] &= \sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} E[J^a|n] \equiv \theta_a, \\ E[J^{a2}] &= \sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} E[J^{a2}|n], \\ E[J^d J^a] &= \sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} n\theta_d E[J^a|n], \\ E[J^{d,1} J^{d,2}] &= \sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} (n\theta_d)(n\theta_d) = 2\theta_d^2 \end{aligned}$$

where we used our assumption that $\omega = 1$, which implies that $\sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} n = 1$ and $\sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} n^2 = 2$. The last but one expression uses the fact that the two jumps are uncorrelated, conditional on a given number of jumps. The last expression computes the expectation of the product of the idiosyncratic jumps for two different stocks. Note that the correlation between these two idiosyncratic jump processes is zero if and only if $\theta_d = 0$, an assumption we make in our calibration.

Dividend Growth and Return Volatility The variance of dividend growth of a firm can be computed as follows

$$\begin{aligned} Var[\Delta d_i] &= (1-p_i)E[\left(\Delta d_i^{ND}\right)^2] + p_i E[\left(\Delta d_i^{D}\right)^2] - \left[(1-p_i)E[\Delta d_i^{ND}] + p_i E[\Delta d_i^{D}]\right]^2, \\ &= (1-p_i)\left[\mu_d^2 + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2\right] \\ &\quad + p_i\left[\mu_d^2 + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2 + E[J^{d^2}] + \lambda_d^2 E[J^{a2}] + 2\lambda_d E[J^d J^a] - 2\mu_d(E[J^d] + \lambda_d E[J^a])\right] \\ &\quad - \left[(1-p_i)\mu_d + p_i[\mu_d - E[J^d] - \lambda_d E[J^a]]\right]^2, \\ &= \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2 + p_i(\delta_d^2 + 2\theta_d^2 + \lambda_d^2 E[J^{a2}] + 2\lambda_d E[J^d J^a]) - p_i^2(\theta_d + \lambda_d\theta_a)^2 \end{aligned}$$

Similarly, mean dividend growth is given by $E[\Delta d_i] = \mu_d - p_i(\theta_d + \lambda_d\theta_a)$. If $\theta_d = 0$, as we assume, mean dividend growth is simply $\mu_d - p_i\lambda_d\theta_a$.

The variance of returns can be derived similarly, with the only added complication that we need to take into account state transitions from i to j that affect the mean return μ_{rij}.

$$\begin{aligned} Var[r_i] &= (1-p_i)E[\left(r_i^{ND}\right)^2] + p_i E[\left(r_i^{D}\right)^2] - \left[(1-p_i)E[r_i^{ND}] + p_i E[r_i^{D}]\right]^2, \\ &= (1-p_i)\left[\sum_{j=1}^{I}\pi_{ij}\mu_{rij}^2 + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2\right] \\ &\quad + p_i\left[\sum_{j=1}^{I}\pi_{ij}\mu_{rij}^2 + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2 + E[J^{d^2}] + \lambda_d^2 E[J^{a2}] + 2\lambda_d E[J^d J^a] - 2\sum_{j=1}^{I}\pi_{ij}\mu_{rij}(E[J^d] + \lambda_d E[J^a])\right] \\ &\quad - \left[\sum_{j=1}^{I}\pi_{ij}\mu_{rij} - p_i(E[J^d] + \lambda_d E[J^a])\right]^2, \\ &= \zeta_{ri} + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2 + p_i(\delta_d^2 + 2\theta_d^2 + \lambda_d^2 E[J^{a2}] + 2\lambda_d E[J^d J^a]) - p_i^2(\theta_d + \lambda_d\theta_a)^2, \end{aligned}$$

where

$$\zeta_{ri} \equiv \sum_{j=1}^{I}\pi_{ij}\mu_{rij}^2 - \left(\sum_{j=1}^{I}\pi_{ij}\mu_{rij}\right)^2,$$

is an additional variance term that comes from state transitions that affect the price-dividend ratio. The volatility of the stock return is the square root of the variance.

Covariance of Returns The covariance of a pair of returns (r^1, r^2) in state i is:

$$\begin{aligned}
Cov[r_i^1, r_i^2] &= (1-p_i)E[r_i^{1,ND} r_i^{2,ND}] + p_i E[r_i^{1,D} r_i^{2,D}] \\
&\quad - \left[(1-p_i)E[r_i^{1,ND}] + p_i E[r_i^{1,D}]\right]\left[(1-p_i)E[r_i^{2,ND}] + p_i E[r_i^{2,D}]\right], \\
&= (1-p_i)\left[\sum_{j=1}^{I} \pi_{ij}\mu_{rij}^2 + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2\xi_d\right] \\
&\quad + p_i\left[\sum_{j=1}^{I} \pi_{ij}\mu_{rij}^2 + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2\xi_d + E[J^{d,1}J^{d,2}] + \lambda_d^2 E[J^{a2}] + 2\lambda_d E[J^d J^a] - 2\sum_{j=1}^{I}\pi_{ij}\mu_{rij}(\theta_d + \lambda_d\theta_a)\right] \\
&\quad - \left(\sum_{j=1}^{I}\pi_{ij}\mu_{rij}\right)^2 - p_i^2(\theta_d + \lambda_d\theta_a)^2 + 2\sum_{j=1}^{I}\pi_{ij}\mu_{rij}(\theta_d + \lambda_d\theta_a), \\
&= \zeta_{ri} + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2\xi_d + p_i(2\theta_d^2 + \lambda_d^2 E[J^{a2}] + 2\lambda_d E[J^d J^a]) - p_i^2(\theta_d + \lambda_d\theta_a)^2,
\end{aligned}$$

where we recall that ξ_d is the fraction of the variance of the Gaussian ϵ shock that is common across all stocks. The correlation between two stocks is the ratio of the covariance to the variance (given symmetry).

Equity Risk Premium By analogy with the derivations above, we have

$$\begin{aligned}
E[J^c] &= \sum_{n=1}^{\infty}\frac{e^{-\omega}\omega^n}{n!}E[J^c|n] = \theta_c, \\
E[J^d J^c] &= \sum_{n=1}^{\infty}\frac{e^{-\omega}\omega^n}{n!}(n\theta_d)(n\theta_d) = 2\theta_c\theta_d, \\
E[J^a J^c] &= \sum_{n=1}^{\infty}\frac{e^{-\omega}\omega^n}{n!}n\theta_c E[J^a|n]
\end{aligned}$$

We also have

$$\begin{aligned}
m^{ND} &= \mu_{mij} - \gamma\sigma_{ci}\eta, \\
m^D &= \mu_{mij} - \gamma\sigma_{ci}\eta + \gamma J^c, \\
\mu_{mij} &= \alpha\log\beta + (\alpha-1)(\kappa_0^c + wc_j - \kappa_1^c wc_i) - \gamma\mu_c,
\end{aligned}$$

The equity risk premium is $-Cov(m, r)$, which can be derived similarly to the covariance between two returns. In particular:

$$\begin{aligned}
Cov[m_i, r_i] &= (1-p_i)E[m_i^{ND} r_i^{ND}] + p_i E[m_i^D r_i^D] \\
&\quad - \left[(1-p_i)E[m_i^{ND}] + p_i E[m_i^D]\right]\left[(1-p_i)E[r_i^{ND}] + p_i E[r_i^D]\right], \\
&= (1-p_i)\left[\sum_{j=1}^{I}\pi_{ij}\mu_{rij}\mu_{mij} - \gamma\phi_d\sigma_{ci}^2\right] \\
&\quad + p_i\left[\sum_{j=1}^{I}\pi_{ij}\mu_{rij}\mu_{mij} - \gamma\phi_d\sigma_{ci}^2 - \gamma E[J^d J^c] - \gamma\lambda_d E[J^a J^c] + \gamma\sum_{j=1}^{I}\pi_{ij}\mu_{rij}\theta_c - \sum_{j=1}^{I}\pi_{ij}\mu_{mij}(\theta_d + \lambda_d\theta_a)\right] \\
&\quad - \left[\sum_{j=1}^{I}\pi_{ij}\mu_{mij} + p_i\gamma\theta_c\right]\left[\sum_{j=1}^{I}\pi_{ij}\mu_{rij} - p_i(\theta_d + \lambda_d\theta_a)\right] \\
&= \zeta_{mi} - \gamma\phi_d\sigma_{ci}^2 - p_i\gamma(2\theta_d\theta_c + \lambda_d E[J^c J^a]) + p_i^2\gamma\theta_c(\theta_d + \lambda_d\theta_a),
\end{aligned}$$

where

$$\zeta_{mi} \equiv \sum_{j=1}^{I}\pi_{ij}\mu_{rij}\mu_{mij} - \left(\sum_{j=1}^{I}\pi_{ij}\mu_{rij}\right)\left(\sum_{j=1}^{I}\pi_{ij}\mu_{mij}\right).$$

A.4 Auxiliary Lemmas

Lemma 1. *Let $x \sim N(\mu_x, \sigma_x^2)$ and $y \sim N(\mu_y, \sigma_y^2)$ with $Corr(x, y) = \rho_{xy}$. Then*

$$E[\exp(ax + by)1_{c>y}] = \Psi(a, b; x, y)\Phi\left(\frac{c - \mu_y - b\sigma_y^2 - a\rho_{xy}\sigma_x\sigma_y}{\sigma_y}\right) \tag{34}$$

where $\Psi(a, b; x, y) = \exp\left(a\mu_x + b\mu_y + \frac{a^2\sigma_x^2}{2} + \frac{b^2\sigma_y^2}{2} + ab\rho_{xy}\sigma_x\sigma_y\right)$ is the bivariate normal moment-generating function of x and y evaluated at (a, b).

Proof. Lemma 1 First, note that $x|y \sim N\left(\mu_x + \frac{\rho_{xy}\sigma_x}{\sigma_y}[y - \mu_y], \sigma_x^2(1 - \rho_{xy}^2)\right)$, therefore

$$E[\exp(ax)|y] = Q\exp\left(\frac{a\rho_{xy}\sigma_x}{\sigma_y}y\right)$$

where $Q = \exp\left(a\mu_x - \frac{a\rho_{xy}\sigma_x\mu_y}{\sigma_y} + \frac{a^2\sigma_x^2(1-\rho_{xy}^2)}{2}\right)$. Denote $\Gamma = E[\exp(ax + by)1_{c>y}]$, then:

$$\begin{aligned}
\Gamma &= E[E\{\exp(ax)|y\}\exp(by)1_{c>y}] \\
&= QE\left[\exp\left(y\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y} + b\right\}\right)1_{c>y}\right] \\
&= Q\int_{-\infty}^{c}\exp\left(y\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y} + b\right\}\right)dF(y) \\
&= Q\int_{-\infty}^{c}\exp\left(y\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y} + b + \frac{\mu_y}{\sigma_y^2}\right\} - \frac{y^2}{2\sigma_y^2} - \frac{\mu_y^2}{2\sigma_y^2}\right)\frac{dy}{\sigma_y\sqrt{2\pi}} \\
&\quad \text{Complete the square} \\
&= Q\exp\left(\frac{\sigma_y^2}{2}\sigma_y\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y} + b\right\}^2 + \mu_y\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y} + b\right\}\right)\int_{-\infty}^{c}\exp\left(-\frac{\left[y - \sigma_y^2\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y} + b + \frac{\mu_y}{\sigma_y^2}\right\}\right]^2}{2\sigma_y^2}\right)\frac{dy}{\sigma_y\sqrt{2\pi}} \\
&\quad \text{Substitute } u = \frac{y - \sigma_y^2\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y} + b + \frac{\mu_y}{\sigma_y^2}\right\}}{\sigma_y},\ du\sigma_y = dy \\
&= \exp\left(a\mu_x + \frac{a^2\sigma_x^2(1 - \rho_{xy}^2)}{2} + \frac{\sigma_y^2}{2}\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y} + b\right\}^2 + b\mu_y\right)\Phi\left(\frac{c - b\sigma_y^2 - a\rho_{xy}\sigma_x\sigma_y - \mu_y}{\sigma_y}\right)
\end{aligned}$$

□

Lemma 2. *Let $x \sim N(\mu_x, \sigma_x^2)$, then*

$$E\left[\Phi\left(b_0 + b_1x\right)\exp\left(ax\right)1_{x<c}\right] = \Phi\left(\frac{b_0 - t_1}{\sqrt{1 + b_1^2\sigma_x^2}}, \frac{c - t_2}{\sigma_x}; \rho\right)\exp(z_1) \tag{35}$$

where $t_1 = -b_1t_2$, $t_2 = a\sigma_x^2 + \mu_x$, $z_1 = \frac{a^2\sigma_x^2}{2} + a\mu_x$, $\rho = \frac{-b_1\sigma_x}{\sqrt{1+b_1^2\sigma_x^2}}$, and $\Phi(\cdot\ ,\cdot\ ;\rho)$ is the cumulative density function (CDF) of a bivariate standard normal with correlation parameter ρ.

Proof. Lemma 2 Denote $\Omega = E\left[\Phi\left(b_0 + b_1 x\right)\exp\left(ax\right)1_{x<c}\right]$, then:

$$\begin{aligned}
\Omega &= \int_{-\infty}^{c}\int_{-\infty}^{b_0+b_1x} \exp\left(ax\right) dF(v) dF(x) \\
&= \int_{-\infty}^{c}\int_{-\infty}^{b_0+b_1x} \exp\left(ax - \frac{v^2}{2} - \frac{\left[x-\mu_x\right]^2}{2\sigma_x^2}\right)\frac{dv\ dx}{\sigma_x 2\pi} \\
&\quad \text{Substitute } v = u + b_1 x,\ dv = du \\
&= \int_{-\infty}^{c}\int_{-\infty}^{b_0} \exp\left(ax - \frac{(u+b_1x)^2}{2} - \frac{\left[x-\mu_x\right]^2}{2\sigma_x^2}\right)\frac{du\ dx}{\sigma_x 2\pi} \\
&= \int_{-\infty}^{c}\int_{-\infty}^{b_0} \exp\left(-\frac{u^2}{2} - x^2\left(\frac{1}{2\sigma_x^2} + \frac{b_1^2}{2}\right) - b_1 ux + 0u + x\left(a + \frac{\mu_x}{\sigma_x^2}\right) - \frac{\mu_x^2}{2\sigma_x^2}\right)\frac{du\ dx}{\sigma_x 2\pi} \\
&\quad \text{Complete the square in two variables using Lemma 3} \\
&= \int_{-\infty}^{c}\int_{-\infty}^{b_0} \exp\left\{\begin{pmatrix} u-t_1 \\ x-t_2\end{pmatrix}'\begin{pmatrix} s1 & s2 \\ s2 & s3\end{pmatrix}\begin{pmatrix} u-t_1 \\ x-t_2\end{pmatrix} + z_1\right\}\frac{du\ dx}{\sigma_x 2\pi} \\
&= \int_{-\infty}^{c}\int_{-\infty}^{b_0} \exp\left(-\frac{1}{2}(U-T)'(-2S)(U-T) + z_1\right)\frac{du\ dx}{\sigma_x 2\pi}
\end{aligned}$$

where $U = (u, x), T = (t_1, t_2), -2S = \begin{pmatrix} 1 & b_1 \\ b_1 & b_1^2 + \frac{1}{\sigma_x^2}\end{pmatrix}, (-2S)^{-1} = \begin{pmatrix} 1 + b_1^2\sigma_x^2 & -b_1\sigma_x^2 \\ -b_1\sigma_x^2 & \sigma_x^2\end{pmatrix}$. This is the CDF for $U \sim N(T, (-2S)^{-1})$. Let $w_1 = \frac{u-t_1}{\sqrt{1+b_1^2\sigma_x^2}}$, $w_2 = \frac{x-t_2}{\sigma_x}$, and $\Sigma = \begin{pmatrix} 1 & \rho \\ \rho & 1\end{pmatrix}$ with $\rho = \frac{-b_1\sigma_x}{\sqrt{1+b_1^2\sigma_x^2}}$. We have that $W' = (w_1, w_2) \sim N(0, \Sigma)$. Also, $du = dw_1\sqrt{1+b_1^2\sigma_x^2}$ and $dx = dw_2\sigma_x$.

$$\begin{aligned}
\Omega &= \exp(z_1)\left\{\int_{-\infty}^{\frac{c-t_2}{\sigma_x}}\int_{-\infty}^{\frac{b_0-t_1}{\sqrt{1+b_1^2\sigma_x^2}}} \exp\left(-\frac{1}{2}W'\Sigma^{-1}W\right)\frac{dw_1\ dw_2}{2\pi\sqrt{1-\rho^2}}\right\}\sqrt{1+b_1^2\sigma_x^2}\sqrt{1-\rho^2} \\
&= \Phi\left(\frac{b_0 - t_1}{\sqrt{1+b_1^2\sigma_x^2}}, \frac{c-t_2}{\sigma_x}; \rho\right)\exp(z_1)
\end{aligned}$$

where we used that $\sqrt{1+b_1^2\sigma_x^2}\sqrt{1-\rho^2} = 1$, and where completing the square implies $t_1 = -b_1 t_2$, $t_2 = a\sigma_x^2 + \mu_x$, $s_1 = -.5$, $s_2 = -.5b_1$, $s_3 = -.5b_1^2 - \frac{1}{2\sigma_x^2}$, and $z_1 = \frac{a^2\sigma_x^2}{2} + a\mu_x$ by application of Lemma 3. ☐

Lemma 3. *Bivariate Complete Square*

$$Ax^2 + By^2 + Cxy + Dx + Ey + F = \begin{pmatrix} x-t_1 \\ y-t_2\end{pmatrix}'\begin{pmatrix} s_1 & s_2 \\ s_2 & s_3\end{pmatrix}\begin{pmatrix} x-t_1 \\ y-t_2\end{pmatrix} + z_1$$

where

$$\begin{aligned}
t_1 &= -(2BD - CE)/(4AB - C^2) \qquad s_1 = A \\
t_2 &= -(2AE - CD)/(4AB - C^2) \qquad s_2 = C/2 \\
z_1 &= F - \frac{BD^2 - CDE + AE^2}{4AB - C^2} \qquad s_3 = B.
\end{aligned}$$

The following lemma will be useful in deriving the variance and covariances of stock returns.

Lemma 4. *Let $Z \sim N(\mu, \sigma^2)$ and define $\phi = \phi\left(\frac{b-\mu}{\sigma}\right)$ and $\Phi = \Phi\left(\frac{b-\mu}{\sigma}\right)$. Then*

$$E[Z1_{Z<b}] = \mu\Phi - \sigma\phi, \tag{36}$$

$$E[Z^2 1_{Z<b}] = \left(\sigma^2 + \mu^2\right)\Phi - \sigma(b+\mu)\phi \tag{37}$$

Proof.

$$E[Z1_{Z<b}] = E[Z|Z<b]Pr(Z<b) = \left(\mu - \frac{\sigma\phi}{\Phi}\right)\Phi = \mu\Phi - \sigma\phi$$

The second result is shown similarly:

$$\begin{aligned} E[Z^2 1_{Z<b}] &= E[Z^2|Z<b]Pr(Z<b) \\ &= (Var[Z^2|Z<b] + E[Z|Z<b]^2)Pr(Z<b) \\ &= \left(\sigma^2 - \frac{\sigma(b-\mu)\phi}{\Phi} - \sigma^2\frac{\phi^2}{\Phi^2} + \left[\mu - \frac{\sigma\phi}{\Phi}\right]^2\right)\Phi \\ &= \left(\sigma^2 + \mu^2\right)\Phi - \sigma(b+\mu)\phi. \end{aligned}$$

□

B Thomson Reuters Business Classification

Thomson Reuters (TR) has developed a market-based business classification system for firms. The system classifies more than 72,000 firms, spread across 130 countries, into one of 837 business activities or 136 different industries. The TR business classification system is widely used. More than 8,000 different indices use the TR business classification system for benchmarking, index computation, and ETF construction.

To classify firms, TR looks at the markets a firm serves. This system is used to classify firms as a whole. If a firm has different business segments, then the business activity of the dominant segment determines the firm's classification. Dominant business segments are identified using revenue, assets, or operating profit thresholds. TR regularly reviews and revises its business classification system to ensure that the business classification assignment for a particular firm remains valid. In this process, over 60,000 firms are reviewed every year.

Further details regarding the business classification system can be obtained from `http://financial.thomsonreuters.com/en/products/data-analytics/market-data/indices/trbc-indices.html`

C Additional Results

In this section, we present additional results and robustness tests.

Results by country: Table A1 and the Figure report the risk-adjusted returns of the Large-minus-Small (LMS) portfolio of financial firms by country. In the Figure, the black solid line presents the cross-sectional average risk-adjusted return and the red line plots the cross-sectional median risk-adjusted return for the LMS portfolio. The risk-adjusted returns are annualized and expressed in percentage.

Banks and financial services firms: Table A2 reports the risk-adjusted returns for the size-sorted portfolios of banks and financial services firms in each country. The table shows the risk-adjusted return for the top and bottom deciles of banks and financial services firms as well as the results separately for emerging and developed markets. Table A3 shows the risk-adjusted returns for the top three commercial banks in each country.

Size effect in financial stock returns: Table A4 compares the performance of large and small financial firms with similar loadings on standard risk factors. For each country, for each financial intermediary in our sample, we estimate loadings on the three Fama-French factors in a given month. For any month, the loadings on the standard risk factors are estimated using data for the prior 12 months. We roll the regression one month at a time to obtain a time series of factor loadings for each financial intermediary in each country in our sample. Next, in each month, for each country, we sort all financial firms into 10 portfolios by loadings on the `SMB` factor. At this time, we also compute the firm Z-score as $Z = std(\beta_{\texttt{Market}}) + std(\beta_{\texttt{HML}})$, where std denotes cross-sectional standardization, for each financial intermediary. Next, in each month, we match a financial firm in the large portfolio to the financial firm in the small portfolio in the same `SMB` decile and with the closest Z-score possible. We form value-weighted returns for all financial firms in the large portfolio and in the small portfolio of matched firms. When there are no small firms in a given `SMB` decile, we assign the risk-free rate. At the end of this exercise, we have monthly value-weighted returns for large and small portfolios of financial firms that differ by market capitalization but have similar loadings on the Fama-French size factor, `SMB`.

Comparison with non-financial firms: Table A5 compares size-sorted portfolio of financial and non-financial firms. Panel A of the table analyzes the relative performance of financial and non-financial firms over different subsamples. Panel B of Table A5 reports the results when financial and non-financial firms are sorted into portfolios using the same decile breakpoints. Finally, Panel C of Table A5 presents the results of financial and non-financial firms sorted by book value of assets. Finally, Table A6 runs a standard characteristics regressions separately for financial firms, banks, and non-financial firms for all countries in our sample.

Results after adjusting for delisting: Table A7 shows the risk-adjusted returns for the size-sorted portfolios of financial and non-financial firms after adjusting for delisting returns. To identify delisted firms in TRD, we use the fact that even after a firm delists, TRD continues to report its monthly total equity return and market capitalization as a stale value that does not vary. We then impute a -100% return to the stock return of all delisted firms so identified. The imputation of a -100% to all delisted firms is equivalent to assuming that all delistings are on account of financial distress or bankruptcy. Finally, we use the data, adjusted for delisting returns, to form the size-sorted portfolios (separately) for financial and non-financial firms in each country.

Alternative portfolio formation schemes: Table A8 shows the risk-adjusted returns for the size-sorted portfolios of financial and non-financial firms after using alternative portfolio formation schemes. In our baseline results we winsorize raw data for stock returns from TRD at the 5^{th} and 95^{th} percentile to remove problematic outliers. There is a chance that winsorization at these levels may exclude a lot of valid return observations which could substantially impact the results. Therefore, in Panel A of Table A8 we rerun the baseline regression for data pooled across all countries after winsorization at the 0.1^{th} and 99.99^{th} percentile levels. Reinganum (1983) shows that small firms experience large returns in Janary and exceptionally large returns during the first few trading days in January. To ensure that the January effect does not drive the fact that large financial firms underperform small financial firms, in Panel B we present the risk-adjusted returns for data pooled across all countries but after excluding all returns for January in each year over our sample period. Finally, in Panel C we confirm that our analysis is unaffected by the use of either value-weighted or equal-weighted portfolio returns.

Sub sample analysis, USD Returns, Additional risk factors, Largest financial firms: Panel A of Table A9 reports the average risk adjusted returns computed using the three-factor Fama-French model over different subsamples. The first two columns report the estimates for the longest available sample for each country. The next two columns restrict to the 1990-2013 sample, while the last two columns restrict to the 2000-2013 sample. Panel B of Table A9 shows the results for returns denominated in U.S. Dollars. When we analyze returns denominated in U.S. Dollars, we use the U.S., the Regional, or the Global Fama-French factors. The U.S. factors are from the model of Fama and French (1993). We also use data for regional Fama-French factors available from Kenneth French's website. The regional factors are available for 4 regions namely, Asia, Japan, Europe, and North America. We apply the corresponding regional factors when we analyze returns denominated in U.S. Dollars for countries located in each of the 4 regions above. Finally, we also use the Global Fama-French factors, data for which is also available from Kenneth French's website. Panel C of Table A9 includes additional risk factors. In addition to the three Fama-French factors, we also include the "Betting against Beta" (BAB) factor from Frazzini and Pedersen (2014), a co-skewness factor from Harvey and Siddique (2000), and the idiosyncratic volatility factor of Ang, Hodrick, Xing, and Zhang (2009). We follow the procedure in Harvey and Siddique to construct the traded co-skewness factor for each country in our sample. Finally, we construct and control for a volatility factor defined as the return to a portfolio that goes long in stocks of financial firms in the bottom decile of idiosyncratic volatility and short in the stocks of financial firms in the top decile of idiosyncratic volatility. Panel D of Table A9 reports the results for the top n financial firms in each country. Each row corresponds to a distinct value of n being 3, 5, or 10, respectively.

Total subsidy to the cost of capital of large financial firms: Table A10 reports the average of this normalized quantity across different groups and time periods. Panel A contains estimates averaged across all countries. In Panel B, we report averages separately for developed and emerging markets. Finally, Panel C collects averages when grouping countries by geographical region.

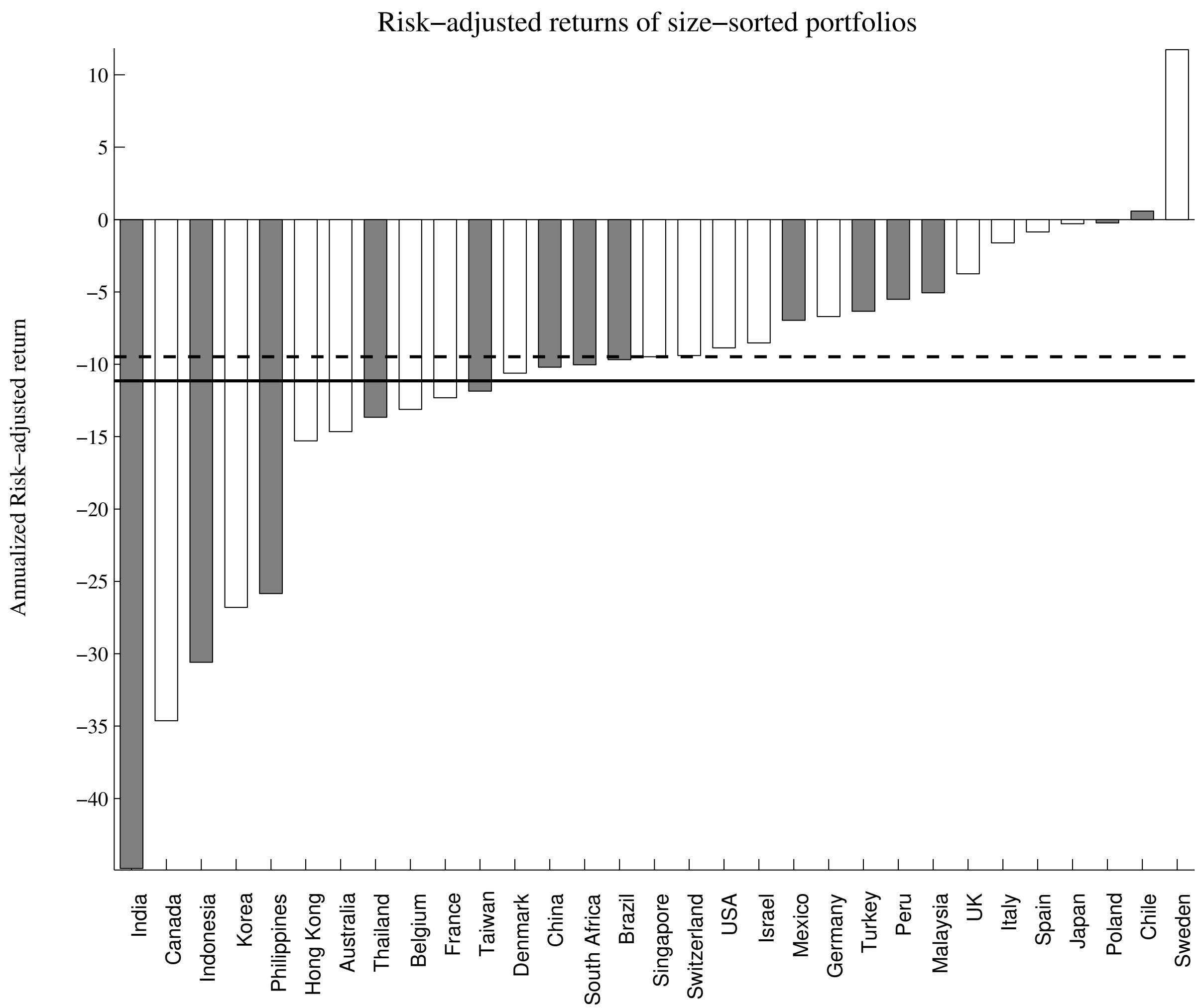

Figure A1. Risk-adjusted returns for size-sorted portfolios of financial firms by country.

This figure presents the risk-adjusted returns of size-sorted portfolios of financial firms by country. In each month, for each country, we sort financial firms into 10 portfolios by market capitalization. Large and small denote the portfolios of firms with the highest and lowest market capitalization, respectively. The figure plots LMS, i.e., the annualized risk-adjusted return of large over small financial firms. All returns are denominated in local currency for each country. The black solid line presents the cross-sectional average risk-adjusted return and the red dashed line presents the cross-sectional median risk-adjusted return for the LMS portfolio. For each country, the longest available sample ending December 31, 2013 is selected.

Table A1. Risk-adjusted returns for size-sorted portfolios of financial firms and non-financial firms by country.

Notes: This table presents the estimates from the pooled OLS regression of monthly excess returns of size-sorted portfolios on equity risk factors. All returns and risk factors are expressed in local currency. In each month, for each country, we sort financial firms and non-financial firms separately into 10 size-sorted portfolios by market capitalization. Large and small denote the portfolios of firms with the highest and lowest market capitalization, respectively. We regress excess returns to large, small, and their difference, denoted LMS, on the Fama and French (1993) risk factors. The table displays the estimates for risk-adjusted return (α) and its t-statistic based on standard errors clustered by time and country. Columns titled `Fin` refer to financial firms, columns titled `Non-fin` refer to non-financial firms, and columns titled `Fin Minus Non-fin` refer to their difference. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Coefficients are annualized, multiplied by 100, and expressed in percentages. For each country, the longest available sample ending December 31, 2013 is selected.

	`Fin`		`Non-fin`		`Fin Minus Non-Fin`	
Country	α	t-stat	α	t-stat	α	t-stat
Australia	-14.66***	-3.63	-11.46***	-6.17	-3.19	-0.79
Belgium	-13.12***	-3.78	5.31***	3.88	-18.43***	-5.00
Brazil	-9.68*	-1.80	8.02***	3.33	-17.70***	-2.69
Canada	-34.63***	-5.38	-26.63***	-10.28	-8.00	-1.30
Chile	0.58	0.19	2.10	1.37	-1.52	-0.39
China	-10.20***	-2.41	-9.95***	-4.50	-0.25	-0.05
Denmark	-10.62***	-3.69	4.80***	3.37	-15.41***	-4.46
France	-12.32***	-3.65	-2.17*	-1.75	-10.14***	-2.80
Germany	-6.71***	-2.42	3.51***	2.58	-10.22***	-2.93
Hong Kong	-15.30***	-2.96	-6.74***	-2.60	-8.56**	-1.97
India	-44.84***	-6.43	-18.89***	-5.66	-25.94***	-4.66
Indonesia	-30.59***	-4.17	-0.87	-0.44	-29.72***	-3.50
Israel	-8.52**	-1.96	-2.78	-1.27	-5.75	-1.38
Italy	-1.61	-0.46	4.54***	3.30	-6.14*	-1.68
Japan	-0.29	-0.09	-4.66***	-4.56	4.38	1.44
Malaysia	-5.06	-1.50	-1.02	-0.49	-4.04	-1.03
Mexico	-6.96	-1.48	4.46***	2.50	-11.42**	-2.12
Peru	-5.51	-0.68	4.17**	1.99	-9.68	-1.19
Philippines	-25.84***	-4.16	-1.84	-1.14	-24.00***	-3.73
Poland	-0.23	-0.02	4.20	0.99	-4.43	-0.35
Singapore	-9.48***	-2.63	-0.85	-0.47	-8.63*	-1.94
South Africa	-10.04***	-2.47	-2.33	-1.27	-7.71	-1.57
South Korea	-26.80***	-4.36	-13.04***	-4.89	-13.76**	-2.14
Spain	-0.85	-0.18	4.42***	2.52	-5.28	-1.00
Sweden	11.74**	2.17	1.08	0.56	10.66*	1.75
Switzerland	-9.40***	-3.87	2.22	1.60	-11.62***	-3.74
Taiwan	-11.85***	-2.47	-3.55**	-2.07	-8.30	-1.37
Thailand	-13.66**	-2.06	-0.67	-0.46	-12.99**	-2.00
Turkey	-6.34	-0.88	0.50	0.18	-6.84	-0.85
UK	-3.75	-1.35	1.42	1.10	-5.17*	-1.92
USA	-8.87***	-2.41	-4.07**	-2.14	-4.80*	-1.68

Table A2. Risk-adjusted returns for size-sorted portfolios of banks and financial services firms only.

Notes: This table presents the estimates from the OLS regression of monthly excess returns of size-sorted portfolios of banks and financial services firms and non-financial firms on equity risk factors. All returns and risk factors are expressed in local currency. In each month, for each country, we sort banks and financial services firms and non-financial firms separately into 10 size-sorted portfolios by market capitalization. Large and small denote the portfolios of firms with the highest and lowest market capitalization, respectively. We regress excess returns to large, small, and their difference, LMS, on the Fama and French (1993) risk factors. In Panel A, for each country we display the estimates for abnormal return (α) for LMS and its t-statistic. In Panel B, we report estimates of α from pooled regressions for: large; small; LMS across all markets; LMS across `developed` markets; LMS across `emerging` markets. Pooled standard errors are clustered by time and country. Columns titled `Fin` refer to banks and financial services firms, columns titled `Non-fin` refer to non-financial firms, and columns titled `Fin Minus Non-fin` refer to their difference. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Coefficients are annualized, multiplied by 100, and expressed in percentages. For each country, the longest available sample ending December 31, 2013 is selected.

	Fin		Non-fin		Fin Minus Non-Fin	
Country	α	t-stat	α	t-stat	α	t-stat
Panel A: Country-level LMS						
Australia	-17.58***	-3.21	-11.44***	-6.15	-6.14	-1.19
Belgium	-17.27**	-2.32	5.42***	3.97	-21.47***	-2.47
Brazil	-6.96	-1.30	7.96***	3.30	-14.92**	-2.27
Canada	-39.92***	-5.30	-26.73***	-10.33	-13.19*	-1.86
Chile	-4.88	-1.31	1.92	1.27	-6.41	-1.44
China	-9.49	-0.89	-9.77***	-4.36	0.23	0.02
Denmark	-16.89***	-4.40	4.71***	3.32	-21.71***	-4.80
France	-14.58***	-3.20	-2.07*	-1.67	-12.50***	-2.61
Germany	-7.54*	-1.76	3.28***	2.45	-10.88***	-2.51
Hong Kong	-10.33*	-1.75	-6.85***	-2.63	-3.54	-0.60
India	-56.52***	-6.12	-18.89***	-5.66	-37.62***	-5.53
Indonesia	-22.54***	-2.40	-0.76	-0.38	-22.15**	-2.00
Israel	-8.97	-1.37	-2.78	-1.27	-6.19	-1.00
Italy	-4.67	-1.22	4.55***	3.30	-9.19**	-2.20
Japan	-0.33	-0.10	-4.66***	-4.56	4.29	1.18
Malaysia	-8.57	-1.26	-1.06	-0.52	-4.69	-0.65
Mexico	-9.87*	-1.74	4.19***	2.35	-13.57**	-2.13
Peru	-16.30*	-1.93	4.15**	1.98	-21.26***	-2.45
Philippines	-22.85***	-2.83	-1.83	-1.13	-21.44**	-2.32
Poland	4.46	0.30	4.00	0.94	0.46	0.03
Singapore	-5.60	-0.93	-0.94	-0.52	-4.52	-0.67
South Africa	-3.10	-0.38	-2.35	-1.27	0.39	0.05
South Korea	-26.95***	-4.23	-13.04***	-4.89	-13.86**	-2.05
Spain	-9.96	-1.49	4.54***	2.61	-16.39**	-2.11
Sweden	3.37	0.30	0.91	0.47	2.63	0.28
Switzerland	-9.34***	-2.88	2.02	1.45	-11.36***	-2.99
Taiwan	-5.52	-0.63	-3.30*	-1.91	-2.96	-0.24
Thailand	-16.39	-1.25	-0.67	-0.46	-14.89	-1.31
Turkey	-4.59	-0.60	0.65	0.23	-5.13	-0.60
UK	-3.72	-1.08	1.42	1.10	-5.14	-1.48
USA	-10.88***	-2.72	-4.07**	-2.14	-6.81**	-2.08
Panel B: Pooled estimates						
Large	-2.02*	-1.81	1.44***	2.84	-3.45***	-2.84
Small	9.48***	3.58	3.99***	3.02	5.24***	2.86
LMS	-11.37***	-4.24	-2.55*	-1.75	-8.65***	-4.51
LMS developed	-11.24***	-4.23	-3.25*	-1.71	-7.76***	-3.97
LMS emerging	-14.00***	-2.52	-1.65	-0.78	-12.43***	-3.30

Table A3. Risk-adjusted returns for top-3 banks only.

Notes: This table presents the estimates from the OLS regression of monthly excess returns of top 3 banks (as measured by market capitalization) on standard stock risk factors by country. All returns and risk factors are expressed in local currency. In each month, for each country, we select the top 3 banks by market capitalization. The table presents the estimates from the OLS regression of monthly excess returns of a value-weighted portfolio of the 3 largest banks on the three Fama and French (1993) stock risk factors i.e. the market, small minus big, and high minus low, respectively. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Coefficients are annualized and multiplied by 100 and expressed in percentages. For the pooled regressions, standard errors are clustered by time and country. For each country, the longest available sample ending December 31, 2013 is selected.

Country	α	t-stat
Panel A: Country-level		
Australia	-4.57*	-1.87
Belgium	-12.77**	-2.07
Brazil	1.69	0.38
Canada	-0.22	-0.13
Chile	14.21***	3.24
China	-0.17	-0.03
Denmark	-14.15***	-4.96
France	-6.23**	-2.09
Germany	-8.09***	-3.51
Hong Kong	3.43	1.24
India	3.40	0.87
Indonesia	-3.37	-0.71
Israel	-0.77	-0.18
Italy	-3.98	-1.33
Japan	-2.11	-0.48
Malaysia	4.71*	1.85
Mexico	9.73**	2.02
Peru	2.57	0.61
Philippines	-0.63	-0.23
Poland	7.29**	2.12
Singapore	0.34	0.16
South Africa	7.66*	1.93
South Korea	-7.09	-1.34
Spain	-2.46	-1.05
Sweden	-2.47	-0.68
Switzerland	-5.96**	-2.41
Taiwan	-9.30***	-2.67
Thailand	0.09	0.02
Turkey	1.19	0.26
UK	-3.54***	-4.38
USA	-10.51***	-3.42
Panel B: Pooled estimates		
developed	-5.16***	-4.47
emerging	3.81**	2.55

Table A4. Risk-adjusted returns for size-sorted portfolios of financial firms matched by risk-factor loadings.

Notes: This table presents the estimates from the pooled OLS regression of monthly excess returns of size-sorted portfolios of financial firms on equity risk factors. All returns and risk factors expressed in local currency. In each month, for each country, we sort financial firms into 10 size-sorted portfolios by market capitalization. Large and small denote the portfolios of firms with the highest and lowest market capitalization, respectively. We regress excess returns to large, small, and their difference, denoted LMS, on the Fama and French (1993) risk factors. The table displays the estimates for risk-adjusted returns (α) and its t-statistic based on standard errors clustered by time and country. The first two columns report the results for the longest available sample for each country, the next two columns report the results over 1990-2013, and the last two columns report the results over 2000-2013. In Panel A, large financial firms are matched to small financial firms in the same `SMB` decile. In Panel B, large financial firms are matched to small financial firms in the same `Market` decile. In Panel C, large financial firms are matched to small financial firms with closest Idiosyncratic Volatility. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Coefficients are annualized, multiplied by 100, and expressed in percentages. For each country, the longest available sample ending December 31, 2013 is selected.

	Full Sample		1990-2013		2000-2013	
	α	*t-stat*	α	*t-stat*	α	*t-stat*
Panel A: Financial firms matched on loadings on `SMB`						
Large	-2.38**	-2.39	-2.52**	-2.39	-2.99**	-2.16
Small	5.20**	5.20	5.38**	2.43	5.92**	2.15
LMS	-7.59***	-7.59	-7.91***	-3.15	-8.91***	-2.82
Panel B: Financial firms matched on loadings on `Market`						
Large	-2.38**	-2.39	-2.52**	-2.39	-2.99**	-2.16
Small	7.85***	3.20	8.19***	3.04	9.46***	2.85
LMS	-10.24***	-3.84	-10.71***	-3.60	-12.45***	-3.32
Panel C: Financial firms matched on Idiosyncratic Volatility						
Large	-2.20**	-2.17	-2.46**	-2.25	-3.00**	-2.13
Small	5.83***	3.03	5.65***	3.03	5.26**	2.30
LMS	-8.04***	-3.75	-8.11***	-3.62	-8.26***	-3.38

Table A5. Risk-adjusted returns for size-sorted portfolios of financial firms and non-financial firms, alternative sorting.

Notes: This table presents the estimates from the pooled OLS regression of monthly excess returns of size-sorted portfolios on equity risk factors. All returns and risk factors are expressed in local currency. In each month, for each country, we sort financial firms and non-financial firms separately into 10 size-sorted portfolios by market capitalization. Large and small denote the portfolios of firms with the highest and lowest market capitalization, respectively. We regress excess returns to large, small, and their difference, denoted LMS, on the Fama and French (1993) risk factors. The table displays the estimates for risk-adjusted returns (α) and its t-statistic based on standard errors clustered by time and country for the LMS and large portfolios for the group of `Fin`, `Non-Fin`, and their difference. The first two columns report the results for the longest available sample for each country, the next two columns report the results over 1990-2013, and the last two columns report the results over 2000-2013. In Panel A, decile breakpoints are specific to each group of firms (i.e. financial and non-financial firms). In Panel B, decile breakpoints are the same across the two groups. In Panel C, decile breakpoints are based on book value. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Coefficients are annualized, multiplied by 100, and expressed in percentages. For each country, the longest available sample ending December 31, 2013 is selected.

	Full Sample		1990-2013		2000-2013	
	α	*t-stat*	α	*t-stat*	α	*t-stat*
Panel A: Different Decile Breakpoints						
LMS						
Fin	-10.47***	-4.50	-10.84***	-4.63	-10.83***	-4.32
Non-fin	-2.52*	-1.72	-2.81*	-1.78	-3.01*	-1.69
Fin minus Non-fin	-7.96***	-4.73	-8.04***	-4.97	-7.82***	-4.35
Large						
Fin	-2.41***	-2.41	-2.54***	-2.41	-3.00**	-2.17
Non-fin	1.46***	2.89	1.33**	2.49	1.37**	2.06
Fin minus Non-fin	-3.86***	-3.50	-3.87***	-3.41	-4.37***	-2.89
Panel B: Same Decile Breakpoints						
LMS						
Fin	-14.22***	-5.19	-15.14***	-5.41	-14.71***	-6.04
Non-fin	-5.05***	-3.07	-5.24***	-3.08	-4.77**	-2.61
Fin minus Non-fin	-9.17***	-5.49	-9.89***	-5.79	-9.94***	-5.81
Large						
Fin	-3.27***	-3.30	-3.59***	-3.44	-4.57***	-3.78
Non-fin	0.34	0.79	0.28	0.68	0.75*	1.77
Fin minus Non-fin	-3.61***	-3.23	-3.88***	-3.35	-5.33***	-3.95
Panel C: Book value sort						
LMS						
Fin	-8.93***	-3.83	-9.18***	-3.93	-11.42***	-5.52
Non-fin	5.51***	6.32	5.65***	5.92	6.16***	5.16
Fin minus Non-fin	-14.44***	-6.68	-14.83***	-6.85	-17.58***	-8.15
Large						
Fin	-4.44***	-4.01	-4.62***	-4.05	-4.83***	-3.70
Non-fin	1.53**	2.46	1.44**	2.23	1.69**	2.18
Fin minus Non-fin	-5.97***	-4.56	-6.06***	-4.49	-6.52***	-3.92

Table A6. Characteristics regression for financial and non-financial firms.

Notes: This table presents the estimates from the pooled OLS regression of annual returns on log of total book value of assets and log market capitalization for each individual company in our sample. The regression includes firm and time fixed-effects. Columns titled `Fin` refer to financial firms, while columns titled `Non-fin` refer to non-financial firms. Panel A reports the results for the longest available sample for each country, Panel B reports the results over 1990-2013, and Panel C reports the results over 2000-2013. `N` denotes the number of observations. Standard errors are clustered at the firm level. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Coefficients are multiplied by 100 and expressed in percentage.

	Fin			Banks			Non-fin		
				Panel A: Full Sample					
Book	-5.20***		-3.62**	-8.56***		-8.14**	-4.18***		-1.95
	(-4.03)		(-2.45)	(-3.31)		(-2.28)	(-3.19)		(-0.87)
Market cap		-5.16***	-2.45		-5.80***	-0.45		-5.28***	-3.73
		(-2.68)	(-1.01)		(-3.71)	(-0.26)		(-3.02)	(-1.31)
N	60,585	60,585	60,585	21,370	21,370	21,370	306,132	306,132	306,132
R^2	2.32	2.22	2.39	4.95	4.27	4.94	1.90	1.98	2.03
				Panel B: 1990-2013					
Book	-5.56***		-4.37***	-9.19***		-7.84**	-4.31***		-2.64
	(-3.70)		(-2.72)	(-2.91)		(-2.01)	(-2.78)		(-1.07)
Market cap		-5.00**	-1.97		-6.55***	-1.56		-4.94***	-2.94
		(-2.24)	(-0.75)		(-3.71)	(-0.26)		(-3.02)	(-1.31)
N	56,389	56,389	56,389	19,883	19,883	19,883	285,790	285,790	285,790
R^2	2.21	1.93	2.16	4.92	4.34	4.94	1.63	1.62	1.70
				Panel C: 2000-2013					
Book	-4.81**		-4.26*	-8.62*		-8.53	-5.27**		-1.94
	(-2.42)		(-1.74)	(-1.67)		(-1.36)	(-2.07)		(-0.52)
Market cap		-3.69	-1.09		-3.71*	-0.13		-5.70**	-4.71
		(-1.29)	(-0.32)		(-1.74)	(-0.05)		(-2.27)	(-4.71)
N	41,515	41,515	41,515	13,570	13,570	13,570	219,689	219,689	219,689
R^2	0.77	0.58	0.77	0.75	0.14	0.75	0.79	0.82	0.82

Table A7. Adjusted for delisting returns.

Notes: This table presents the estimates from the OLS regression of monthly excess returns of size-sorted portfolios on equity risk factors. All returns and risk factors are expressed in local currency. In each month, for each country, we sort financial firms and non-financial firms separately into 10 size-sorted portfolios by market capitalization. Large and small denote the portfolios of firms with the highest and lowest market capitalization, respectively. In all cases, we adjust for delisting returns by imputing a return of -100% for all firms that delist during our sample for whatever reason. We regress excess returns to large, small, and their difference, denoted LMS, on the Fama and French (1993) risk factors. Columns titled `Fin` refer to financial firms, columns titled `Non-fin` refer to non-financial firms, and columns titled `Fin Minus Non-fin` refer to their difference. In Panel A, we report the estimates for risk-adjusted return (α) for LMS and its t-statistic for each country. In Panel B, results are reported when pooling across all countries, across developed markets only, and across emerging markets only. For pooled data, t-statistic based on standard errors clustered by time and country. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Coefficients are annualized, multiplied by 100, and expressed in percentages. For each country, the longest available sample ending December 31, 2013 is selected.

	`Fin`		`Non-fin`		`Fin Minus Non-Fin`	
Country	α	t-stat	α	t-stat	α	t-stat
Panel A: Country-level LMS						
Australia	-12.49***	-3.03	-12.08***	-6.52	-0.41	-0.10
Belgium	-10.94***	-2.36	2.30	1.43	-13.25***	-2.65
Brazil	-11.76**	-2.00	4.09*	1.63	-15.85**	-2.15
Canada	-33.83***	-5.25	-25.66***	-9.80	-8.17	-1.32
Chile	2.47	0.51	1.47	0.85	1.00	0.20
China	-10.20***	-2.41	-10.26***	-4.62	0.06	0.01
Denmark	-12.38***	-3.61	3.64**	2.10	-16.02***	-3.83
France	-9.79***	-2.94	-1.65	-1.24	-8.15**	-2.14
Germany	-6.38*	-1.83	3.39**	2.14	-9.77***	-2.58
Hong Kong	-15.55***	-2.99	-6.71***	-2.55	-8.84**	-2.04
India	-43.03***	-6.01	-17.60***	-5.56	-25.44***	-4.38
Indonesia	-31.29***	-4.18	-0.32	-0.16	-30.97***	-3.58
Israel	-8.25*	-1.86	-3.48*	-1.62	-4.76	-1.10
Italy	1.42	0.39	3.53***	2.47	-2.12	-0.52
Japan	-0.61	-0.19	-4.28***	-4.04	3.67	1.15
Malaysia	-5.40	-1.59	-1.95	-0.91	-3.44	-0.86
Mexico	-4.40	-0.62	1.16	0.61	-5.56	-0.77
Peru	7.62	0.75	-1.21	-0.40	8.82	0.85
Philippines	-25.50***	-4.04	-2.93*	-1.74	-22.57***	-3.46
Poland	0.57	0.05	4.45	0.93	-3.88	-0.30
Singapore	-8.59**	-2.31	-2.49	-1.31	-6.11	-1.33
South Africa	-4.78	-0.98	-4.14**	-2.15	-0.64	-0.12
South Korea	-23.39***	-3.55	-13.10***	-4.89	-10.29	-1.52
Spain	2.49	0.31	1.03	0.49	1.46	0.20
Sweden	11.46**	2.20	-2.15	-0.92	13.61**	2.19
Switzerland	-10.13***	-3.96	-0.52	-0.32	-9.60***	-2.90
Taiwan	-11.77***	-2.40	-3.57**	-2.07	-8.20	-1.32
Thailand	-12.88*	-1.95	-1.14	-0.77	-11.73*	-1.80
Turkey	-4.94	-0.65	0.28	0.10	-5.22	-0.63
UK	-0.13	-0.05	3.78***	2.62	-3.91	-1.36
USA	-6.39*	-1.82	-1.63	-0.86	-4.76*	-1.67
Panel B: Pooled estimates						
Large	-4.01***	-3.86	-0.40	-0.78	-3.61***	-3.08
Small	5.10**	2.29	2.71**	2.03	2.39*	1.73
LMS	-9.11***	-3.85	-3.11**	-2.29	-6.00***	-3.53
LMS developed	-8.14***	-3.28	-3.58**	-1.99	-4.56***	-2.66
LMS emerging	-12.38***	-2.81	-2.63	-1.42	-9.75***	-3.00

Table A8. Alternative portfolio formation schemes.

Notes: This table presents the estimates from the pooled OLS regression of monthly excess returns of size-sorted portfolios on equity risk factors. All returns and risk factors are expressed in local currency. In each month, for each country, we sort financial firms and non-financial firms separately into 10 size-sorted portfolios by market capitalization. Large and small denote the portfolios of firms with the highest and lowest market capitalization, respectively. We regress excess returns to large, small, and their difference, denoted LMS, on the Fama and French (1993) risk factors. The table displays the estimates for risk-adjusted return (α) and its t-statistic based on standard errors clustered by time and country. Columns titled `Fin` refer to financial firms, columns titled `Non-fin` refer to non-financial firms, and columns titled `Fin Minus Non-fin` refer to their difference. Results are reported when winsorizing raw returns data from TRD at 0.1^{th} and 99.99^{th} percentile levels (Panel A), excluding all data for January in each year (Panel B), and using equal-weighted portfolio returns (Panel C). Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Coefficients are annualized, multiplied by 100, and expressed in percentages. For each country, the longest available sample ending December 31, 2013 is selected.

	`Fin`		`Non-fin`		`Fin Minus Non-Fin`	
	α	*t-stat*	α	*t-stat*	α	*t-stat*
Panel A: Winsorization at 0.1^{th} and 99.99^{th} percentile levels						
Large	-2.41**	-2.41	1.46***	2.89	-3.86***	-3.50
Small	8.07***	3.75	3.98***	3.01	4.09***	2.93
LMS	-10.47***	-4.50	-2.52*	-1.72	-7.96***	-4.73
Panel B: Excluding January returns						
Large	-2.32**	-2.11	1.49***	2.68	-3.81***	-3.16
Small	6.46***	3.29	3.36***	2.67	3.10***	2.39
LMS	-8.78***	-4.01	-1.86	-1.31	-6.91***	-4.29
Panel C: Equal-weighted returns						
Large	-1.81**	-2.01	1.29***	2.54	-3.10**	-3.16
Small	10.00***	4.47	4.59***	3.23	5.41***	3.81
LMS	-11.81***	-4.89	-3.30**	-2.10	-8.51***	-5.22

Table A9. Robustness tests.

Notes: This table presents the estimates from the pooled OLS regression of monthly excess returns of size-sorted portfolios of financial firms on equity risk factors. All returns and risk factors expressed in local currency. In each month, for each country, we sort financial firms into 10 size-sorted portfolios by market capitalization. Large and small denote the portfolios of firms with the highest and lowest market capitalization, respectively. We regress excess returns to large, small, and their difference, denoted LMS, on the Fama and French (1993) risk factors. The table displays the estimates for risk-adjusted return (α) and its t-statistic based on standard errors clustered by time and country. The first two columns report the results for the longest available sample for each country, the next two columns report the results over 1990-2013, and the last two columns report the results over 2000-2013. Panel A reports the results for the baseline model. In Panel B returns and risk factors expressed in USD and the risk factors are either the US, or Regional, or Global Fama-French factors. In Panel C, returns and risk factors are expressed in local currency, and the risk factors are the standard Fama and French (1993) factors augmented by either the "Betting against Beta" factor from Frazzini and Pedersen (2014), the co-skewness factor from Harvey and Siddique (2000), and a Volatility factor that goes long financial firms in the bottom decile of idiosyncratic volatility and short financial firms in the top decile of idiosyncratic volatility, or all three together. In Panel D, the large portfolio is constructed using the top n financial firms. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Coefficients are annualized, multiplied by 100, and expressed in percentages. For each country, the longest available sample ending December 31, 2013 is selected.

	Full Sample		1990-2013		2000-2013	
	α	*t-stat*	α	*t-stat*	α	*t-stat*
Panel A: Baseline model						
Large	-2.41***	-2.41	-2.54***	-2.41	-3.00**	-2.17
Small	8.07***	3.75	8.30***	3.81	7.83***	3.35
LMS	-10.47***	-4.50	-10.84***	-4.63	-10.83***	-4.32
Panel B: USD-denominated returns						
USD, U.S. FF3	-11.75***	-4.75	-11.72***	-4.50	-9.74***	-3.66
USD, Regional FF3	-11.06***	-4.56	-11.26***	-4.57	-11.14***	-4.26
USD, Global FF3	-10.88***	-4.37	-11.13***	-4.40	-9.79***	-3.90
Panel C: Additional risk factors: BAB, Co-Skewness, and Volatility Factor						
BAB	-10.40***	-4.13	-10.67***	-4.20	-10.51***	-3.91
Co-Skew	-10.40***	-4.46	-10.63***	-4.54	-10.74***	-4.28
Vol	-11.08***	-4.46	-11.51***	-4.51	-11.57***	-4.33
BAB, Co-Skew, Vol	-10.94***	-4.11	-11.14***	-4.16	-11.03***	-3.91
Panel D: Top n financial firms						
$n = 3$	-1.62*	-1.77	-1.78*	-1.74	-2.72***	-2.74
$n = 5$	-1.77**	-2.18	-1.85**	-2.06	-2.41***	-2.89
$n = 10$	-1.94**	-2.22	-1.99**	-2.07	-2.16***	-2.41

Table A10. Total subsidy to the cost of capital for large financial firms

Notes: This table presents the estimates for the total subsidy to the cost of capital for Large financial firms. In each month, for each country, we sort financial firms into 10 size-sorted portfolios by market capitalization. Large and small denote the portfolios of firms with the highest and lowest market capitalization, respectively. We regress the difference in the return to large minus small, denoted LMS, on the Fama and French (1993) risk factors separately for each country. The risk-adjusted return (α) from this regression is multiplied by the average market capitalization of firms in the large portfolio and is normalized by the gross domestic product of the country as of December 2013. The first column reports the results for the longest available sample for each country. The next column reports the results over 1990-2013, and the last column reports the results over 2000-2013. Panel A reports the average subsidy across all countries. Panel B reports the average subsidy for developed and emerging markets. Panel C reports the average subsidy across geographic regions. For each country, the longest available sample ending December 31, 2013 is selected.

Market	Full Sample	1990-2013	2000-2013
Panel A: All countries			
All countries	-2.68	-2.76	-3.45
Panel B: MSCI Classification			
developed	-3.64	-3.82	-5.39
emerging	-1.52	-1.47	-1.08
Panel C: By Region			
Americas	-2.28	-2.44	-3.36
Asia-Pacific	-5.11	-5.23	-6.22
Europe	-0.49	-0.48	-0.84
Middle East	-1.10	-1.10	-1.18