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Equity is Cheap for Large Financial Institutions: The International Evidence
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ABSTRACT

Equity is a cheap source of funding for a country's largest financial institutions. In a large panel of 31 countries, we find that the stocks of a country's largest financial companies earn returns that are significantly lower than stocks of non-financials with the same risk exposures. In developed countries, only the largest banks' stock earns negative risk-adjusted returns, but, in emerging market countries, other large non-bank financial firms do. Even though large banks have high betas, these risk-adjusted return spreads cannot be attributed to the risk anomaly. Instead, we find that the large-minus-small, financial-minus-nonfinancial, risk-adjusted spread varies across countries and over time in ways that are consistent with stock investors pricing in the implicit government guarantees that protect shareholders of the largest banks. The spread is significantly larger for the largest banks in countries with deposit insurance, backed by fiscally strong governments, and in common law countries that offer shareholders better protection from expropriation. Finally, the spread predicts large crashes in that country's stock market and output.

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

1 Introduction

There is a wealth evidence from credit markets that implicit government guarantees lower the borrowing costs of large financial institutions (see, e.g. Acharya, Anginer, and Warburton (2013) for recent evidence). In a recent study, the GAO (2014) found that 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. Our paper shows that at least some of these guarantees were perceived to significantly benefit the shareholders of the largest banks in developed countries as well as the shareholders of the largest non-bank financials in emerging markets. As a result, we conclude that equity is a cheap source of funding for the largest financial institutions around the world. The size of these effects depends on the country's institutional and macroeconomic characteristics.

Government guarantees that are extended to financial institutions absorb risk that is otherwise borne by their creditors and shareholders. These guarantees reduce not only the risk that financial stocks are exposed to, but can also affect the residual return that is left after applying the standard risk adjustment. In the Gandhi and Lustig (2015); Kelly, Lustig, and Van Nieuwerburgh (2016) bailout-augmented dynamic asset pricing model, which builds on the rare event models of Gabaix (2012a); Wachter (2013); Backus, Chernov, and Martin (2011), the average risk-adjusted returns earned on financial stocks that benefit from guarantees are low during normal times in anticipation of the bailouts of shareholders in disaster states. In this class of models, firm and country characteristics that determine the likelihood and size of bailouts also predict risk-adjusted returns on financial stocks. We find empirical evidence in a large panel of countries that support these predictions of the model.

This paper makes two main contributions. Our first contribution is to establish that the size anomaly in financial stock returns in the U.S. markets is pervasive in other stock markets. This eliminates sampling error in the measurement of expected returns on U.S. bank stocks as an explanation of Gandhi and Lustig (2015)'s findings. We find that the size effect for financial stock returns is robust across a broad sample of international developed and emerging markets. The U.S. experience is not an outlier. In a large sample of 31 developed and emerging market countries, the stock returns of the largest financial firms in a country have been puzzlingly low over long periods of time. The difference in average risk-adjusted returns between the extreme size decile portfolios of financial firms within a country is -10.47% per year. For non-financials, this difference is only -2.52% per year. The magnitude of the effect is much stronger in the second half of our sample, and especially in the years prior to the credit crisis of 2007.[1] The critical size threshold seems to be the 90th size percentile in a country. Financial institutions that exceed this threshold earn negative risk-adjusted returns that are statistically and economically significant.

We also uncover significant differences between developed and emerging markets. In developed markets, much of the spread is attributable to the largest banks. In developed countries, only the largest banks in the top size decile deliver negative risk-adjusted returns (-3.29% per annum). We did not detect a similar effect for the largest insurance and real estate companies. By contrast, in emerging markets, the spread is mainly attributable to negative risk-adjusted returns for large non-bank financial firms such as real estate investment companies.

Consistent with stock markets pricing 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 (2012a); Wachter (2013)), an increase in the probability of a 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.[2]

Our key contribution is to explore the panel dimension by relating the differences in the average risk-adjusted return on the size-sorted portfolios of financial firms for each country to the regulatory,

[1]The size spread is not larger for financial than non-financial firms in only two countries out of a sample of 31 (Japan and Sweden).

[2]We also verify large financial firms fare much better during economic crises in developed countries, even though they are more levered than their smaller counterparts. 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, whereas the corresponding number for the top 10th decile is only 0.20%.

policy, and institutional framework within each country. These cross-sectional effects are not consistent with mispricing or behavioral biases, but instead point to rational pricing of government guarantees. For banks, the risk-adjusted large-minus-small return spread is 12% per annum larger in countries with deposit insurance. The magnitude of the risk-adjusted large-minus-small return spread increases with the fiscal health of the government in a particular country. Implicit bailout guarantees are only credible if governments have the resources to back up these promises. In earlier work, Acharya, Drechsler, and Schnabl (2014) found that European bank CDS spreads were highly correlated with sovereign risk of their country of origin during the 2008 crisis. Our results indicate that sovereign risk is always a large determinant of bank stocks valuations, even before crises.

Finally, the magnitude of the large-minus-small spread is significantly higher in countries with a common law legal system. The existing literature (for example, La Porta, Lopez-De-Silanes, and Shleifer (2002)) shows that shareholders are perceived to be better protected from expropriation in common law countries. Governments in common law countries may be unable –within the bounds of the law– or reluctant to wipe out the shareholders of large financial institutions in the process of a bailout. There are some recent precedents to support this notion. Recently, the U.S. courts ruled that the Federal Reserve had illegally taken a large equity stake in A.I.G. in 2008, thus expropriating its shareholders[3], 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.

This is truly a size effect rather than a market capitalization effect (see Berk (1997) for a discussion of this distinction). When we run regressions of returns on firm characteristics, the book value of assets turns out to be the key determinant of returns for financial firms, but not for non-financial firms. The largest financial firms, measured by book value, earn returns that are 5.97% lower than the largest non-financial firms.[4] The large-minus-small financials-minus-non-financials spread is minus 14.44%. Quantitatively, 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,

[3]NYTimes, June 15, 2015

[4]This also means that we are not simply picking up short-term reversal effects in the market cap sorts.

we see that over the entire sample, the implied 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 USD terms, the size of the annual subsidy is highest for Asia ($1,356 billion), then for Americas ($759 billion), followed by Europe ($129 billion) and Middle East ($17 billion). Furthermore, unlike, e.g., the momentum anomaly, this anomaly does not rely on sophisticated dynamic trading strategies. Loading on this anomaly also requires very limited turnover, which implies that adjusting for transaction costs would arguably have very limited effect on its magnitude. Except during financial crises, there is no evidence to suggest that shorting large financial firms is costlier than shorting large non-financial firms.

Large financial institutions do have high betas and higher systematic volatility, as one would expect if management maximizes the value of the menu of put options granted by the government. However, 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 (Frazzini and Pedersen (2014)) explanation. Large financial firms earn low returns even when matched against large non-financial firms with the same betas and idiosyncratic volatility. In addition, the returns on the largest financial firms do no co-vary with Frazzini and Pedersen (2014)'s betting against beta factors.

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 share prices of large bank stocks. Instead, we find evidence that equity is actually always a cheap source of funding for the largest banks in a country. There is no obvious behavioral explanation of our findings.

The remainder of this paper is organized as follows: Section 2 reviews the related literature.

Section 3 describes a bailout-augmented dynamic asset pricing model, based on Kelly, Lustig, and Van Nieuwerburgh (2016). We use this model to derive some testable implications. Section 4 describes the data set, and explains how we construct portfolios of financial firms sorted by size as measured by market capitalization and book value. Section 5 establishes that there is size anomaly in financial stock returns around the world. Section 6 relates the size anomaly to legal, economic, policy and regulatory environment within a country. Finally, section 7 concludes.

2 Related literature

There is a large literature on size effects in stock returns (see Banz (1981), Basu (1983), Lakonishok, Shleifer, and Vishny (1994), Fama and French (1993), Berk (1997) and others), but most of these papers do not include financial stocks, presumably because of their high leverage. Gandhi and Lustig (2015) are the first to document that the size effect in bank stocks in the US is really about size, rather than market capitalization. They show that the size anomaly in the financial sector is consistent with government guarantees that protect shareholders of large, but not small, financial firms in disaster states. We show that the size anomaly for financial sector stock returns in the US is robust to concerns regarding bank definition. Further, we extend the analysis in their paper to a set of 31 countries and show that the financial sector size anomaly is not unique to the US. Finally, a panel of 31 countries allows us to tie cross-sectional variation in the magnitude of the size anomaly to the regulatory, legal, and institutional framework within countries.

In a recent paper, Gandhi and Lustig (2015) (GL hereafter) show that the largest commercial bank stocks in the U.S. have significantly lower risk-adjusted returns than small banks. The size anomaly for U.S. bank stock returns is large. 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.[5] GL provide circumstantial evidence that attributes

[5]While GL present a lot of circumstantial evidence, that in the end makes the case, they present no direct empirical evidence tying the size anomaly specifically to the conjectured economic source - i.e. the implicit guarantees provided by governments to shareholders of large but not small financial banks during financial crisis.

the U.S. size anomaly in bank stock returns to implicit guarantees that benefit shareholders of the largest banks. Our paper looks at the international evidence and uses cross-country variation in the bank stock return spread to identify its fundamental determinants.

There is direct evidence from option markets that tail risk in the financial sector is priced differently. Kelly, Lustig, and Van Nieuwerburgh (2016) find that the out-of-the-money index put options of bank stocks were relatively cheap during the recent crisis, as a consequence of the government absorbing sector-wide tail risk. In related work on bank stock returns, Fahlenbrach, Prilmeier, and Stulz (2012) document that those banks that incurred substantial losses during previous crises were more likely to incur losses during the recent crisis. If some banks benefit from a larger perceived tail risk subsidy, they have an incentive to load up on this type of risk. 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 find some evidence that banks whose managers' interests were more aligned with shareholders actually performed worse during the recent financial crisis. Our work contributes to the important task of measuring systemic risk in the financial sector. Acharya, Brownless, Engle, Farazmand, and Richardson (2011), Acharya, Pedersen, Philippon, and Richardson (2011), Adrian and Brunnermeier (forthcoming), and Huang, Zhou, and Zhu (2009) develop novel methods for measuring systemic risk.

3 Model with Financial Disaster Risk

We provide a simple model of financial crises and bailouts, based on Kelly, Lustig, and Van Nieuwerburgh (2016). Financial crises are periods of elevated risk of a financial disaster, modeled in the Barro (2006a); Rietz (1988a) tradition. The model features both Gaussian and tail risk. We model the collective government guarantee as a floor on the fall in aggregate bank losses that the government tolerates in a financial disaster. Through this truncation, the government eliminates part of the sector-wide 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.

The critical difference between banks and other non-financial corporations is their susceptibility to bank 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 consider banking panics or financial disasters as a source of aggregate risk. To model the asset pricing impact of financial disasters, we use a version of the Barro (2006a); Rietz (1988a); Longstaff and Piazzesi (2004) asset pricing model with a time-varying probability of disasters, as developed by Gabaix (2012a); Wachter (2013); Gourio (2008). The model features two sources of priced risk: Gaussian risk and financial disaster (tail) risk. While non-financial corporations are also subject to the aggregate risk generated by financial disasters, their exposure is more limited and they do not (or at least much less) enjoy the collective bailout guarantee that supports the financial sector.

3.1 Environment

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

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:

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

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:

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

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

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. However, 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:

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

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.[6] Finally, we allow for heteroscedasticity in the Gaussian component of consumption growth: σ_{ci} depends on the Markov state i.

[6]Note that when J^c is activated, we have already conditioned on a disaster occurring. 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.

Dividends of Individual Firms in Financial Sector In state $i \in \{1, 2, \ldots, I\}$, the dividend process of an individual bank is given by:

$$
\begin{aligned}
\Delta d_{t+1} &= \mu_d + \phi_d \sigma_{ci} \eta_{t+1} + \sigma_{di} \epsilon_{t+1}, \quad \text{if no disaster} \\
\Delta d_{t+1} &= \mu_d + \phi_d \sigma_{ci} \eta_{t+1} + \sigma_{di} \epsilon_{t+1} - J^d_{t+1} - \lambda_d J^a_{t+1}, \quad \text{if disaster}
\end{aligned}
$$

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 in the calibration 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 banks. It has an idiosyncratic component J^d and a common component J^a. The parameter λ_d governs the exposure of the bank 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 banks, 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 $-\lambda_d E[J^a]$.

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 banking sector. The common component of the loss rate becomes the minimum of the maximum tolerated sector-wide loss rate $\underline{J}$ and the actual realized aggregate loss rate J^r:

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

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

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:

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

where ND (D) denotes the Gaussian (disaster) component of consumption growth, dividend growth or returns. We define "resilience" for the consumption claim as: $H^c_t = 1+p_t\left(E_t\left[\exp\left\{(\gamma-1)J^c_{t+1}\right\}\right]-1\right)$. The Euler equation simplifies to:

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

We define the log resilience as:

$$\begin{aligned} h^c_t &\equiv \log(H^c_t) = \log\left(1+p_t\left[\exp\left\{\bar{h}^c\right\}-1\right]\right), \\ \bar{h}^c &\equiv \log E_t\left[\exp\left\{(\gamma-1)J^c_{t+1}\right\}\right] = \omega\left(\exp\left\{(\gamma-1)\theta_c + .5(\gamma-1)^2\delta^2_c\right\}-1\right), \end{aligned}$$

where we used the cumulant-generating function to compute $\bar{h}^c$. It is now clear that resilience only varies 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:

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

If we define "resilience" for the dividend claim as: $H^d_t = 1+p_t\left(E_t\left[\exp\left\{\gamma J^c_{t+1} - J^d_{t+1} - \lambda_d J^a_{t+1}\right\}\right]-1\right)$, then the Euler equation simplifies to:

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

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

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

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:

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

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 $e^{n(-\lambda_d\theta_r + .5\lambda_d^2\delta_r^2)}$. Hence, in the no-bailout case, the resilience is given by:

$$
\bar{h}^d = \omega\left(\exp\left\{\gamma\theta_c - \theta_d - \lambda_d\theta_r + .5(\gamma^2\delta_c^2 + \delta_\theta^2 + \lambda_d^2\delta_r^2)\right\} - 1\right)
$$

An increase in bailout protection always increases the resilience of the stock.

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 the appendix. All else equal, an increase in the bailout (smaller $\underline{J}$) tends to increase the resilience of the stock and lowers the expected return in a non-disaster sample. In particular, a large bank stock that benefits from a bailout has negative risk-adjusted returns when benchmarked against small bank 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 large risk-adjusted returns in a 'normal sample'.

An increase in the probability of a disaster lowers the dividend yield on the stock with the highest resilience by less. We will check this prediction of the model 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 approximately given 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 the appendix. 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 bank stocks has predictive power for large drops in the stock market and GDP.[7]

4 Data and summary statistics

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 that are included in either the MSCI Developed or the MSCI Emerging Markets index. We further restrict our 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 is available for at least three years.

[7]In sections A of 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 banks.

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 sample ends in December 2013.

In TRD, we identify financial firms by means of the `sector` variable. This variable is based on the Worldscope Industry Classification Benchmark (ICB) codes.[8] ICB allocates a company to that 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 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`).

Conventional wisdom suggests that the implicit government guarantees that protects shareholders of large firms, but not small firms, in disaster states primarily impacts commercial banks. However, we cast a wide net by focusing on all financial firms for two reasons. First, there are significant differences across countries in the way in which banks and financial services firms are organized. In the US, 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, and hence restricting the sample to firms with sector values equal to banks seems inappropriate for the US. 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[9].

Second, in the US 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

[8] `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.

[9] 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.

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 show that the size anomaly is at least three times as large for banks and financial services firms as compared to the size anomaly for insurance and real estate investment services firms.[10]

We eliminate all observations for which 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. We winsorize the price-to-book value at zero. 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 pairs of consecutive observations that have total equity returns that exceed (fall below) 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 potentially corrupt and set the return for this firm in January and February 2013 to be missing. All these changes are necessary given the poor data quality in TRD.

We identify delisted firms using the fact that 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 identify the first month of these stale value series as the month in which the firm delists. Data for firms that delist during our sample period are excluded only after the month in which they delist. Thus, for firms that delist in January of any year, we set the monthly total equity returns, market capitalization, and price-to-book values as missing starting only from February of

[10]It should be possible for a researcher to identify commercial banks in TRD by a manual search to eliminate (include) irrelevant (relevant) firms in the sample. However, this approach is not feasible given that we analyze more than 30 years of monthly data across 31 countries.

that year. This ensures that the returns properly account for delistings. We also exclude data for all firms that are inactive throughout our sample period. This assumes that the investor liquidated his holdings of that firm at the final listed price. We check to confirm that our results are robust when we allow for worse outcomes (i.e. assume that the investor lost all his holdings at the time of delisting).

As a final step, we remove all observations for which the firm name includes the word fund, mutual funds, income, and income fund. This filter ensures that our results are not driven by mutual funds or other such investment services. In all countries, we exclude very small firms as measured by market capitalization by eliminating 10% of the firms with the lowest market capitalization. Our final dataset consists of 1,418,532 observations for 31 countries. Note that 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.

Our filter works well in identifying financial firms. We compared our list of US 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. Our list from TRD includes firms that account for 80.71% of the total book value of assets of the top 100 bank holding companies in the US. The FDIC considers Macy's, Nordstrom, Apple Financial Holdings, United Services Automobile Association as bank holding companies. DataStream (correctly) does not identify these firms as banks or any other kind of financial firms because that is not their primary business function. Similarly, the FDIC identifies BBVA, Deutsche bank, HSBC and Barclays as large US bank holding companies. Our list includes these firms in their country of incorporation and does not count these as bank holding companies incorporated in the US.

Table 1 presents the list of countries in our sample and the number of unique financial firms available throughout our sample for each country. For each country in our sample, the table lists the classification (Developed vs Emerging), the start year for the data, the number of unique financial firms, the percentage of publicly listed firms that are classified as financial firms, and the percentage of market cap for all financial firms as a percentage of total market capitalization for all firms. There is substantial cross-sectional variation in the number and size of financial firms across countries. For example, in Japan and Taiwan, approximately 9% of the firms are classified as financial firms and account for less than 20% of the market capitalization, while in Hong Kong, nearly 34% of firms are classified as financial firms and these firms account for approximately 50% of the market capitalization. The number of unique financial firms also varies by country. The US has the largest number of unique financial firms at 3,201, followed by India at and the United Kingdom at 778. The South American countries Chile and Peru have the lowest number of unique financial firms at 67 and 55, respectively. The 3,201 unique financial firms in the US account for just 13.16% of the entire market capitalization. On the other hand, the 82 financial firms in Belgium account for nearly 36% of the market capitalization. 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 by 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 based on their market capitalization. We then calculate the value-weighted returns for each of these deciles for each country for February 2013. In February 2013, we again rank all financial intermediary stocks in each country by market capitalization. In each country, the stocks are again allocated to deciles based on their market capitalization. We calculate the value-weighted returns for each of these deciles 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 our entire sample.

Table 2 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. In the table, `Large` and `Small` denote the portfolios of firms with the highest and lowest market capitalization, respectively, and `LMS` denotes the return of `Large` minus `Small`. `N` is the average number of unique financial firms; `Fcap` is the average market capitalization of financial firms as a percentage of market capitalization of the entire financial intermediary sector; `%Turn`, the turnover ratio, is the probability (in %) that a firm migrates to another portfolio in the subsequent month. `Ret` denotes the average value-weighted monthly return. Here and throughout our subsequent tables, we annualize average returns by multiplying by 12 and express them in percentages.

Table 2 shows that firms in the first decile account on average for 0.20% to 0.40% of the market capitalization of the entire financial intermediary sector. On the contrary, the largest financial firms account for a stunning 66% figure for Emerging markets and as much as 76% for Developed markets. Thus, it appears that the financial intermediary sector is concentrated, with the bulk of the market capitalization held by the largest financial companies. The number of unique financial firms in the `Small` portfolio in a given country averages at 143, while it is much lower for the `Large` portfolio at 46. This pattern is mimicked by the turnover ratio, as only about 3% of `Large` financial firms migrate to another portfolio in the subsequent month compared to an already modest 13% figure for the `Small` portfolio. This evidence has important implications for our asset pricing tests as it implies that a portfolio strategy that goes long the `Large` while shorting the `Small` portfolios would be subject to very limited turnover. The last two columns of Table 2 show that, on average, large financial firms underperform small financial firms by 7.84% across all countries, significant at the 1% level. The return to `LMS` is -3.74% for Developed markets and much larger at -14.77% for Emerging markets. This large difference is mainly originating from the `Small` portfolio, whose return turns out to be about 15% higher for Emerging markets.

To visualize the country-level estimates, we plot in Figure 1 the average return on the `LMS` portfolio by country, sorted in ascending order. We note a high degree of cross-sectional variation in the performance of `LMS`. The figure also confirms the result from Table 2 of significant differences across Emerging (white bars) and Developed (black bars) markets. In particular, the 4 countries with the lowest `LMS` are Emerging markets. Only 7 out of 31 countries feature positive `LMS` average returns, with Sweden having the highest and sole significantly positive performance at 20.56%. A natural question that arise is how much of this return differentials can be explained by exposure to standard risk factors, which is the topic we turn next.

5 Size effect in risk-adjusted stock returns

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 bonds and stocks while large financial firms underperform.

5.1 Risk-adjusted returns on financial intermediary stock portfolios

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 `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`, the local value factor `HML` and the local market factor `Market` in local currency by using the six value-weighted portfolios of all stocks in that country sorted by size and book-to-market. Thus our vector of risk factors includes: $\boldsymbol{f}_t = [\texttt{Market}\,\texttt{SMB}\,\texttt{HML}]$.

We estimate 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 3. The columns titled `Fin` report the estimates for financial firms. Since 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 in the same country. To form the size-sorted portfolios of non-financial firms, we apply the standard portfolio formation strategy of Fama and French (1993) described above 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.[11]

Panel A of Table 3 reports the estimate when pooling the data across all countries. We note that the portfolio of largest financial firms delivers a negative risk-adjusted return of -2.41% in annual terms (t-stat of -2.41) compared to a positive 8.07% figure for small financials (t-stat of 3.75). These numbers imply that the risk-adjusted return to the `LMS` portfolio for financial firms in our sample averages at -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 performance of size-sorted financials is in stark contrast with that of non-financial firms. For the latter, risk-adjusted returns for both large and small firms are positive at 1.46% and 3.98%, respectively. The alpha of the `LMS` for non-financials is therefore much more modest at -2.52%, significant at the 10% level. Taken together, the `LMS` for financials delivers an abnormal return that is about 8% lower than non-financial firms. Nearly half of this figure is due to the `Large` portfolio of financials delivering a 3.86% lower risk-adjusted return than a `Large` portfolio of non-financials. In short, stocks of large financial firms seem consistently overpriced compared to a benchmark of non-financial firms of the same size, even after adjusting for exposure to the market, value, and size factors.

Panel B and Panel C report the estimates when pooling the data across Developed and Emerging markets, respectively. A few interesting facts emerge. First, the abnormal performance of the `LMS` portfolio of financials is comparable at -9.47% for Developed and -13.82% for Emerging countries. When benchmarking these numbers to the `LMS` portfolio of non-financials, however, the risk-adjusted performance is almost double for Emerging markets at -12.21% compared to the -6.26% figure for Developed markets. Both numbers are statistically and economically highly significant. Second, much of the risk-adjusted performance of `LMS` for Developed markets originates from the underperformance of the `Large` portfolio, which delivers a large and significant -4.31% abnormal return compared to non-financials. Third, the majority of the underperformance of `LMS`

[11] In Appendix Table CI we report the individual country estimates.

for Emerging markets can be traced to a the 8.51% abnormal return of the `Small` portfolio, with the remaining -3.70% coming from the `Large` portfolio.

Note that the results in Table 3 do not take delisting returns into account if the stock for any firm in our sample simply stops trading publicly for whatsoever reason. The primary reason for this is that, unlike standard datasets for the US, TRD does not provide us with the return on a stock on the date it is removed from the listed stock exchange. In fact, TRD does not even identify firms that are delisted during any given month. Accounting for delisting returns is important, as the extant literature shows that the magnitude of empirical asset pricing anomalies can be sensitive to the treatment of delisting returns. Adjusting for delisting returns is also important if the delisting rates for financial firms are different from those of non-financial firms, and if the delisting rates are a function of firm size.[12] To check if our results are robust to delisting returns, we begin by identifying the set of delisted firms in TRD. 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.[13] Finally, we use this new data series (with the -100% imputed returns for delistings), to form the size-sorted portfolios (separately) for financial and non-financial firms in each country. Table CII in Appendix C shows that delisting returns hardly impact our result. The return on the `LMS` portfolio for financial firms drops from -10.47 in Table 3 to -9.11 in Table CII and is still statistically significant at the 1% level or better.

To sum up, Gandhi and Lustig (2015) have recently documented a large size anomaly in US commercial bank stock returns. Taken together, the results in this section show that the US experience with regards to the size anomaly in the financial sector is robust and not unique,

[12]For example, Gandhi and Lustig (2015) show that in the US, the delisting rate of small banks is higher than the delisting rate of large banks by a factor of 10.

[13]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 finds that more than half the delistings are on account of mergers and acquisitions not related to financial distress.

although the magnitude of the effect differs across the groups of Developed and Emerging markets.

5.2 Subsample and robustness analysis

We analyze time variation in the size anomaly for financial firms and check whether it is robust to controlling for loadings on additional risk factors. We also investigate the role of the very largest financial firms in each country and look at results for financial firms sorted by the kind of business they are engaged in.

5.2.1 Robustness to different sample periods

We begin by examining time variation in the size of the abnormal performance to the `LMS` portfolio. Panel A of Table 4 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, and coincide with those in Panel A of Table 3. The next two columns restrict to the 1990-2013 sample, while the last two columns restrict to the 2000-2013 sample. The results indicate that the size anomaly is quite robust. While over the longest available sample for each country, a long-short position 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% over the entire sample, the loss on this long-short portfolio increases to 10.84% over 1990-2013 and to 10.83% over 2000-2013. What is interesting to notice is that the progressively more negative performance of `LMS` is attributable to the underperformance of the largest financial firms being increasing over time from -2.41% for the full sample to -3.00% for 2000-2013. In contrast, the `Small` portfolio consistently outperforms the benchmark portfolio of stocks by about 8% in all periods.

5.2.2 Robustness to risk-factor loadings

To show more forcefully that for financial firms actual size does matter, we directly contrast the performance of large and small financial firms with similar loadings on standard risk factors. To do this, we proceed as follows: As a first step, for each country, for each financial intermediary in our sample, we estimate the 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.[14] 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`. Panel B in Table 4 reports the average risk-adjusted returns for the `Large`, matched `Small` and `Large` minus matched `Small` portfolios. This long-short portfolio looses about -7.59% in risk-adjusted terms per year over the entire sample. This number, although 2.88% smaller than the risk-adjusted number for the size-sorted deciles, is still statistically and economically significant.

Panel C of Table 4 presents a similar exercise for financial firms matched on the `Market` factor. That is, we contrast the risk-adjusted return for financial firms that differ in market capitalization but have similar market betas. Now the LMS portfolio looses about -10.24% in risk-adjusted terms per year over the entire sample. This number 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 the standard risk factors.

Ang, Hodrick, Xing, and Zhang (2009) show that, in the U.S. as well as across several international markets, firms with high idiosyncratic volatility earn lower average returns compared to 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,

[14]In those cases when there are no small firms in a given `SMB` decile, we assign the risk-free rate.

we match Large financials to Small financials with the closest idiosyncratic volatility, computed as the standard deviation of the residuals in the rolling regression on the three Fama-French factors. Panel D of Table 4 contains the corresponding results. We find that Small financials still outperform Large financials with comparable idiosyncratic volatility by a full 8% on a risk-adjusted basis throughout all sample periods considered.

5.2.3 Robustness to additional risk factors

Table CIII in appendix C shows that our results our robust to the inclusion of additional risk factors. In Table CIII, in addition to the three Fama-French factors, we also include the "Betting against Beta" 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). The rationale for these additional risk factors is as follows: Larger financial firms are more levered and have higher market betas. Frazzini and Pedersen (2014) already document that a long-short portfolio that goes long in high-beta stocks and short in low-beta stocks generates significant negative risk-adjusted returns. In addition, by granting the 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. Harvey and Siddique (2000) show that co-skewness is priced in the cross-section of US stock returns. Finally, Baker and Wurgler (2015) argue that the low risk anomaly is present in U.S. banks and could be linked to the degree of leverage. We construct a volatility factor as the return to a portfolio that goes long financials in the bottom decile of idiosyncratic volatility and short financials in the top decile of idiosyncratic volatility. As is clear from Panel B, our results are essentially unchanged. The annual return on the LMS portfolio is still large at -10.94% when all additional factors are included (-11.03% in the most recent sample), and highly statistically significant.

5.2.4 Results for the largest financial firms

In Panel E of Table 4, we report 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. 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 3 financial firms by size account for nearly 67% of the risk-adjusted return for the largest financial firms. The loss for the largest 3 financial firms has increased to -2.72% over the 2000-2013 sample, compared to -2.16% for the largest 10 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.

5.2.5 Results for the largest financial firms by type

In Table 4, we evaluate the performance of the `Large` portfolio of financial firms based on the type of business they are engaged in. That is, for each country we separately analyze the returns of size-sorted portfolios of firms classified as 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 sample, the abnormal 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 annum in risk-adjusted terms. In contrast, the annual risk-adjusted return on the portfolio for insurance firms is -1.44% (not statistically significant). The last row in Panel D shows that for real estate firms, the risk-adjusted return on the portfolio is -2.07%, only marginally statistically significant.

Gandhi and Lustig (2015) attribute the size anomaly in bank stock returns for the US to implicit guarantee provided to large financial firms but not to small financial firms in disaster states. Later, in section 6 we will also relate the size anomaly in financial stock returns to this implicit guarantee. In most countries, especially 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, often, do not enjoy the same level of protection. Given this background, it may appear surprising that large real estate investment firms also deliver negative abnormal returns. To dig deeper into this finding, we separately analyze Developed and Emerging markets in Panels B and C, respectively. Our evidence confirms that indeed much of the underperformance of Developed markets is concentrated on 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), while the risk-adjusted on insurance firms is -1.35% (not statistically significant) and the risk-adjusted return on real estate firms is -1.30% (not statistically significant). Further, while the risk-adjusted return on banks is decreasing monotonically over 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).

The presence of a statistically significant loss for a long-short portfolio for financial firms other than banks and financial services can also be explained by the fact that there are important differences in the manner in which banks and financial services firms are 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 an implicit government guarantee and are considered too-big-to-fail. However, in many other countries the largest financial firms as measured by market capitalization may be insurance or real estate investment services.

Tables CIV and CV in appendix C provide further results for the largest financial firms or financial firms sorted by the type of business they engage in. While Table CIV shows the results for size-sorted portfolios of firms that are classified as banks and financial services firms *only*, Table CV presents the results for the top 3 largest commercial bank in each country. When we restrict our sample to just banks and financial services firms the risk-adjusted return on the `LMS` portfolio increases to -11.37% and this is again statistically significant at the 1% level or better. Table CV shows that, when we restrict our sample to just the largest banks in each country, the risk-adjusted returns is on average -5.16% for developed markets and +3.81% for emerging markets. Thus, it appears that there are important differences in the size anomaly across emerging and developed markets. There may 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. We return to this argument in section 6 below.

5.3 Financial versus non-financial firms

In Table 6, we provide further analysis for the comparison between size-sorted portfolio of financial versus non-financial firms. We first examine time variation in the abnormal return to `LMS` and to the `Large` portfolio in Panel A. The first column of the panel corresponds to the estimates in Table 3. We note that the `Fin minus Non-Fin` abnormal performance has been rather stable over different sample periods at about -8%. Panel A also shows that the underperformance of `Large` financial firms relative to `Large` non-financial firms that increasingly accounts for the largest portion of this spread. By 2000-2013, of the total spread between financial and non-financial firms of -7.82%, -4.37% (or more than half) can be traced to firms in the top decile.

Our analysis thus far was conducted by separately sorting financial and non-financial firms into market capitalization deciles. To make the results more directly comparable, we sort all financial and non-financial firms into 10 size bins using the deciles breakpoints based on the market capitalization of *all* traded stocks (i.e. both financial and non-financial firms) within a particular country. We then apply these common decile breakpoints to separately form size-sorted portfolios of financial and non-financial firms. Panel B of Table 6 reports the corresponding results. By design, the financial and non-financial firms in each portfolio are roughly of the same size. The results show that the value-weighted, risk-adjusted return for financial firms in the last size bin are 14.22% lower than those in the first bin. For non-financial firms, the magnitude of the size anomaly is -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 magnitude of the anomaly for financial firms is at least three times larger than the magnitude of the anomaly for non-financial firms.

Figure 2 compares the risk-adjusted return of financial firms to that of non-financial firms belonging to the same decile. That is, to construct the figure, we essentially compare the risk-adjusted return of financial firms to those of non-financial firms in decile i, for each country in our sample.[15] The figure plots the average risk-adjusted return of financial firms relative to that of non-financial firms for each decile across all 31 countries in our sample. While the largest financial firms underperform the largest non-financial firms by an average of 3.41%, the converse is true for the smallest firms in any country. In other words, small financial firms are considered relatively risky as compared to small non-financial firms. Figure 2 also shows that while the differences are most stark for the extreme deciles, the relative mispricing of financial firms is nearly monotonically decreasing from decile 1 to decile 10. Even firms in decile 9 are relatively mispriced as compared to non-financial firms. For decile 9, the risk-adjusted difference is nearly -1.5% per annum and is marginally statistically significant. This result is expected given the possibility of mergers. Even if it is only the very largest financial firms that benefit directly from implicit government guarantees, because of mergers, some of the effects will contaminate expected risk-adjusted returns of smaller banks.

Finally, Panel C presents the results of financial and non-financial firms sorted by book value of assets. The rationale for this analysis is as follows: Market cap measures size, but it also measures expected returns. Firms that generate more cash flows will tend to have higher market capitalization, but firms with lower expected returns, holding cash flows constant, also have larger market capitalization. As a result, Berk (1997) argues that there should be a relation between expected returns and 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. Panel C shows that the pattern in risk-adjusted returns when sorting by book value of assets is similar to that obtained when sorting by the market capitalization, and is in fact even stronger than the one documented in Panel A. For non-financial

[15] As described above, financial and non-financial firms are still sorted into deciles separately.

firms, there is no evidence of a size anomaly when firms are sorted by book value of assets. In fact, 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 a stunning -14.44%.

The results for the portfolio sort by book value reveal that for financial firms actual size as measured by its book value seems to be a key determinant of its returns. That is, larger financial firms have negative abnormal returns. Table 7 confirms this evidence by running the standard characteristics regressions separately for financial firms, banks, and non-financial firms for all countries in our 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 statistically significant negative coefficient for log book value (-5.20%) as well as for market capitalization (-5.16%). These coefficients are significant at the 1% level. However, when we include both log book value and market capitalization, we note that the coefficient on book value for financial firms is at least 4 times as large as the coefficient on market value. Further, the coefficient on market capitalization is not significant. These results suggest that a 100% increase in the book value of financial firms above the sample average lowers annual returns by nearly 400 basis points for a typical financial firm, holding market capitalization fixed.

The columns titled banks in Table 7 show that a similar affect exists for banks. For banks, size measured by both book value and market capitalization is negatively correlated with returns. However, once we control for book value, the relationship between size as measured by market capitalization and returns is not statistically significant. In most cases the coefficient on book value is at least 9 times as large as the coefficient on market capitalization.

The last column reports the results for nonfinancial firms. For nonfinancial firms, size as measured by market capitalization drives out any relationship between book value and returns.Over our entire sample the coefficient on market capitalization is nearly twice as large as the coefficient on book value, although both these coefficients are not 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.

As a further check, we also compare the risk-adjusted return on Large financials to that on a set of Large nonfinancials that are similar along various dimensions of risk. In particular, in analogy to Panel B and D of Table 4 we match Large financials to Large nonfinancials based alternatively on the loadings on the `Smb` factor or idiosyncratic volatility. In untabulated results, we find that Large nonfinancials still significantly underperform Large nonfinancials on a risk-adjusted basis by -6.50% (when matching on `Smb`) to -3.50% (when matching on idiosyncratic volatility).

6 What is the size anomaly in financial stock returns?

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. In this section, 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.

6.1 Performance of the size anomaly in economic and market downturns

If large financial institutions benefit from the government implicit guarantee, we should also expect that the performance of the `LMS` portfolio, while negative on average, should peak (i.e. turn positive) during crises periods when large firms are in fact shielded. We investigate whether this is indeed the case in Table CVI, which collects the returns to the `LMS` portfolio during an economic or financial crisis. 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 fall below the 10th percentile for that country. If there are consecutive quarters that meet this criteria 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 Panel A of the table displays the average performance of this investment over all economic and financial crisis in each of the 31 countries 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.

The Table 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. increases during economic or financial contractions). We attribute this performance to differences in shareholder recovery rates on these portfolios during economic or financial disaster states. 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 small financial firms (in realized returns).

The performance of the `LMS` portfolio during an economic and financial crisis may partly be attributed 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 allow individual small financial firms to regularly go under. Therefore, the last three columns in Table CVI 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 respective portfolios at the start of the economic or financial crisis. The table shows that on average, nearly 1% of the firms in the bottom 10th decile fail during an economic crisis, whereas the corresponding number for the top 10th 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 crisis across all 31 countries in our sample. The corresponding number for large financial firms is 30.

Table CVI also highlight clear differences in the performance of the `LMS` portfolio during crisis between Developed and Emerging markets. 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, that result from the implicit bailout guarantee provided by regulators to shareholders of large firms. These differences may be closely related to the legal, economic, policy, regulatory and institutional framework that exist within a particular country, which is the topic we turn next.

6.2 The size anomaly forecasts economic and market downturns

In the event of a financial crises (typically defined as events during which a country's financial sector experiences runs, sharp increases in financial sector default rates accompanied by large losses of capital that result in public intervention, bankruptcy, or forced merger of financial institutions), 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 US but for most developed and emerging markets included in our samples.[16]

The existence 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 standard rare events asset pricing model, developed by Rietz (1988b) and Barro (2006b), and extended by Gabaix (2012b) and Wachter (2008), 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 small 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

[16] 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 even shareholders of large financial institutions.

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 US data, there is a strong connection between the business cycle and the incidence of financial crisis.[17] Therefore, we begin by studying 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. In these respects, the international nature of our data is ideal to carry this type of analysis. As long as financial crises are not perfectly correlated across countries, the panel structure would enhance our identification and increases the power of our test.

Table 8 presents the estimates from a panel conditional fixed-effect logit regression. The dependent variable is a dummy variable that takes the value 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 `LMS` increases i.e. the expected return on the `LMS` portfolio becomes more negative. This in turn implies that that the difference between the dividend yield of large and small financial firms should become 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 the GDP. A 1% increase in the expected return gap increases the odds of a 10% drop in the stock market over the next 3 months by nearly 13% and that of a 10% drop in GDP by approximately 10%. Thus, the size anomaly in financial firms returns appears to be a

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

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.

6.3 Size anomaly and the institutional framework

In this section, we relate the size 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 regulatory, policy, and institutional framework within each country. Note that if the size anomaly for financial firms is an extension of the "market capitalization" effects documented in the literature for non-financial firms, then ex-ante we do not expect the time-series or the cross-sectional variation in the magnitude of the anomaly to be related to variables that measure the legal, institutional, regulatory, or policy environment.

Table 9 examines the relation between the size anomaly and the legal environment in a country using a standard panel regression framework. The explanatory variables are: `Legal`, which is a dummy variable that equals 1 if the country follows a common law system and zero otherwise; `Governance` and `Creditor`, which measure the strength of the corporate governance and credit rights within a particular country, respectively. The data for `Governance` is from La Porta, Lopez-de Silanes, Shleifer, and Vishny (2000), while the data for the creditor right index are from López de Silanes, La Porta, Shleifer, and Vishny (1998). For the countries in our sample these variables do not vary over time. Countries with stronger corporate governance and stronger creditor rights have a higher score for the `Governance` and `Creditor`, respectively. In columns 1-4 of Table 9, the dependent variable is the risk-adjusted return for the `LMS` portfolio measured on 5-year non-overlapping windows. In columns 5-8, the dependent variable is the risk-adjusted return for large banks and financial services firms measured on the same sample periods. We include time fixed effects in each regression and compute clustered standard errors.

The results in Table 9 show that the magnitude of the anomaly is higher in countries with a common law legal system, while it is lower in countries with a higher score on the corporate governance or the creditor rights index. The higher subsidy (more negative) 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.[18]

Table 9 also shows that, as expected, the magnitude of the size anomaly is inversely related to corporate governance and creditor rights. 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 banks would attenuate the magnitude of the anomaly. Acharya, Amihud, and Litov (2011) show that stronger corporate governance and credit rights are one such mechanisms. In particular, Acharya, Amihud, and Litov (2011) show that firms in countries with strong corporate governance and creditor rights do not take as much risk as compared to firms in other countries. Thus, the fact the magnitude of the size anomaly is inversely related to corporate governance and creditor rights is consistent with the hypothesis that it is a manifestation of the implicit government guarantees. A negative association between corporate governance and bank risk taking is also suggested by Laeven (2002) who shows that banks with more concentrated ownership take more risks as compared to banks with diverse ownership.

Table 10 relates the magnitude of the size anomaly to the financial environment or development in a country. In this regression, `Deposit` is a dummy variable that equals 1 if the country has deposit insurance and is zero otherwise, `Borrow` is the percentage of the population in a particular country that has borrowed from a bank and hence indicated the depth of bank penetration within a particular country, `Bank Credit/GDP` is the ratio of bank credit to GDP. Data for bank credit is from Baron and Xiong (2015). Note that for a given country, the ratio of bank credit to GDP varies over time which allows us to include country fixed-effects in the corresponding regression

[18]Existing literature (for example, La Porta, Lopez-De-Silanes, and Shleifer (2002)) shows that governments in countries with French, German, Scandinavian or socialist legal systems have a higher tendency to intervene in economic activity than governments in countries with a common law legal system. Our results show that, when it comes to financial firms, the opposite is true. Markets 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 larger extent that governments located in countries with other kinds of legal systems.

specification. The layout of Table 10 is the same as Table 9 with the first 4 columns showing the results for all financial firms and the last 4 columns showing the results for banks and financial services firms.

The results indicate that the magnitude of the size anomaly is higher in countries with deposit insurance, although the result is statistically significant only when we measure the size anomaly for banks and financial services firms. This is sensible as deposit insurance is a policy that only impacts deposit-taking institutions. Insurance firms and real estate finance firms typically do not offer deposit services to their customers. The negative and statistically significant coefficient on the dummy for deposit insurance is evidence that the size anomaly for banks is different from the market capitalization effects for non-financial firms. The higher prices (lower expected returns) for banks located in countries with deposit insurance relative to financial firms in countries without deposit insurance is consistent with O'Hara and Shaw (1990) who show a positive wealth effect for shareholders of banks that are considered "too-big-to-fail" in the US. Demirguc-Kunt and Detragiache (2002) also find that explicit deposit insurance increases risk taking by financial firms and increases the likelihood of a financial crisis. An increase in the likelihood of a financial crisis would again be manifested by an increase in the magnitude of the size anomaly and the tail risk insurance provided to large banks.

The remaining columns in Table 10 show that more dependent the economy in a particular country is on banks, the larger is the magnitude of the size anomaly for financial firms. For countries where a higher percentage of the population accesses bank credit or where the size of the banking sector as measured by the ratio of bank credit to GDP is high, we observe a larger gap between the risk-adjusted returns of large and small financial firms. Although the coefficients on `Borrow` or `Bank Credit/GDP` are not always statistically significant, they have the right sign.

A large literature (for example se Panageas (2010) and Acharya, Drechsler, and Schnabl (2014), among others) suggests a link between sovereign and financial sector credit risk. In many countries, this link arises naturally because of government bailouts to financial firms in the event that the financial sector becomes distressed. Ex-post, the explicit cost of such bailouts weakens government finances and gives rise to a positive correlation between financial sector and sovereign credit risk. However, ex-ante, if the size anomaly is driven by implicit bailout guarantees, and if the link between the financial sector and sovereign credit risk is priced in by investors, we should observe that the magnitude of the size anomaly is larger for countries in better fiscal health.

Table 11 uses the panel regression framework to relate the size anomaly to `Surplus`, which is the ratio of the budget surplus or deficit for a particular country to its GDP, and to `Spread`, which is the spread on the long-term government bond issued by a particular country over the yield on the long-term bond issued by the U.S. Treasury. In Table 11, `Currency` is a dummy variable that equals 1 if the country in question is facing a currency crisis at any time during the period over which the risk-adjusted returns for `LMS` is measured.

The results indicate that the better the fiscal health of the government, measured by either a lower surplus to GDP ratio or a lower spread on the sovereign long-term bond, the larger the magnitude of the size anomaly (i.e. the spread between `Large` and `Small` firms). This effect is consistent with the view that the size anomaly is driven by implicit bailout guarantees, and that the link between the financial sector and sovereign credit risk is priced in expected returns to financials. A 1% increase in the ratio of budget surplus to GDP is associated with a -3.75% increase (i.e. more negative) in the spread between large and small financial firms. Similarly, an increase in the spread on the long-term bond issued by the government, i.e. a worsening of the government fiscal health, is associated with a decline in the magnitude of the size anomaly.The spread is much larger during currency crises.

Finally, Table 12 relates the size anomaly to the response of regulators and policymakers to past financial crises for the countries in our sample. When a financial crisis break, regulators and policymakers have two broad approaches available to them. The first, which we refer to as an accommodating 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 depositors and creditors of financial firms. The alternative approach is to restore depositor confidence but 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 accommodating approach to financial crisis in the past, investors would increasing expect such intervention in future financial crises as well, and this would be reflected in a larger magnitude of the size anomaly for financial firms (given that it is driven in part by implicit bailout guarantees to large financial firms).

Table 12 reports estimates for the effect of past financial crisis resolution policies on the size anomaly for financial firms. The explanatory variables are a dummy variable (`Bank`), which equals 1 if the country has suffered a banking crisis in the past three years and zero otherwise; `Nationalize`, which equals 1 if some of the financial firms in the country were nationalized in response to the crisis; `AssetPurchase`, which equals 1 if bad assets were purchased from financial firms; `Combined`, which equals 1 if the financial firms in the country were restructured, recapitalized, or provided with a blanket guarantee, in the past three years. `Surplus` measures the budget surplus of the country as a ratio of the GDP. Finally, `Support` measures the cost of the fiscal support provided to the financial sector in the past three years. Data for these variables is from the Systemic Banking Crisis Database provided by International Monetary Fund.[19] We interact `Nationalize`, `AssetPurchase`, and `Combined` with the dummy variable `Bank` and `Support` with `Surplus` to capture the additional effect on the abnormal return to `LMS` of the type of government intervention, conditional on a crisis.

We find that accommodating regulatory policies strengthen the investors belief that large financial firms will be supported in the event of a financial crisis. These beliefs manifest themselves as a higher gap in the average risk-adjusted return to `LMS`. The strongest effect is seen for bank nationalization as this makes explicit the implicit guarantees provided to banks in the event of financial disasters. The expectation of investors is also linked to how credible is the backing provided by the government for the financial sector. Indeed, the coefficient on the cost of fiscal support to the banking sector interacted with the budget surplus of the country is negative and statistically significant at the 10% level. Thus, implicit bailout guarantees are more believable and their effects more pronounced when words can be backed with action.

[19] This database is maintained by Fabian Valencia and Luc Laeven and is available at https://www.imf.org/external/pubs/cat/longres.aspx?sk=26015.0.

In closing this section, 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 magnitude of the anomaly and the legal, policy, regulatory, and institutional framework within a particular country. In appendix C, we confirm that these results primarily hold for financial firms and not non-financial firms in the countries in our sample. Overall, the institutional framework captures a substantial fraction of the cross-sectional and time-series variation in the size anomaly in the financial sector.

6.4 Size anomaly and the tail risk insurance to large financial firms

The evidence in the previous three subsections suggests that 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. In this section, we offer 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 resultant 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 GDP of the country as of December, 2013.

Table 13 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 contains 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 to Developed markets is always greater than that of Emerging markets. In the most recent sample, the difference is quite significant, with Developed markets averaging 5.39% of GDP compared to a 1.08% figure for Emerging countries. In USD terms, these differences appear even more stark if we consider that the average GDP of Developed markets in our sample is $2,270 billion in December 2013, while the corresponding number for Emerging markets is only \$206.63 billion. Finally, Panel C collects averages when grouping countries by geographical region. We note that the size of the subsidy is the highest for the countries located in Asia Pacific, followed by countries located in the Americas, Middle East, and Africa. In USD terms, the size of the subsidy is highest for Asia (\$1,356 billion), then for Americas (\$759 billion), followed by Europe (\$129 billion) and Middle East (\$17 billion).

As a final remark, it is worth noting that our estimates of the subsidy only measure the impact of tail risk insurance on the cost of equity capital. Since financial institutions are highly levered, even if the direct effect on the overall cost of capital may be small, the indirect effect would be not: since shareholders are last in line, the implied subsidy to other bank creditors would be even larger.

7 Conclusion

There is an active debate about whether banks should be forced to have 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, 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 notion that leverage-constrained investors inflate 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 a large panel of 31 countries, we find that the stocks of a country's largest financial companies earn returns that are significantly lower than stocks of non-financials with the same risk exposures. In developed countries, only the largest banks' stock earns negative risk-adjusted returns, but, in emerging market countries, other large non-bank financial firms do. The large-minus-small, financial-minus-nonfinancial, risk-adjusted spread varies across countries in ways that are consistent with stock investors pricing in the implicit government guarantees that protect shareholders of the largest banks in developed countries. The spread is significantly larger for the largest banks in countries with deposit insurance, backed by fiscally strong governments, and in common law countries that offer shareholders better protection from expropriation.

References

Acharya, Viral V, Yakov Amihud, and Lubomir Litov, 2011, Creditor rights and corporate risk-taking, *Journal of Financial Economics* 102, 150–166.

Acharya, Viral V, Deniz Anginer, and A Joseph Warburton, 2013, The end of market discipline? investor expectations of implicit state guarantees, *December). www. papers. ssrn. com/sol3/papers. cfm.*

Acharya, Viral V., Christian Brownless, Robert Engle, Farhang Farazmand, and Matthew Richardson, 2011, *Measuring Systemic Risk, Regulating Wall Street: The Dodd-Frank Act and the New Architecture of Global Finance* (John Wiley and Sons, Inc.).

Acharya, Viral V., Itamar Drechsler, and Phillip Schnabl, 2014, A pyrrhic victory? bank bailouts and sovereign credit risk, *The Journal of Finance* 69, 2689–2739.

Acharya, Viral V., Lasse Pedersen, Thomas Philippon, and Matthew Richardson, 2011, *Taxing Systemic Risk, Regulating Wall Street: The Dodd-Frank Act and the New Architecture of Global Finance (John Wiley and Sons, Inc., New York, NY).* (John Wiley and Sons, Inc., New York, NY).

Admati, Anat R, Peter M DeMarzo, Martin F Hellwig, and Paul C Pfleiderer, 2011, Fallacies, irrelevant facts, and myths in the discussion of capital regulation: Why bank equity is not expensive, *MPI Collective Goods Preprint*.

Adrian, Tobias, and Markus K. Brunnermeier, forthcoming, Covar, *American Economic Review*.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2009, High idiosyncratic volatility and low returns: International and further u.s. evidence, *Journal of Financial Economics* 91, 1–23.

Backus, David, Mikhail Chernov, and Ian Martin, 2011, Disasters implied by equity index options, *Journal of Finance* forthcoming.

Baker, Malcolm, Brendan Bradley, and Jeffrey Wurgler, 2011, Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly, *Financial Analysts Journal* 67, 40–54.

Baker, Malcolm, and Jeffrey Wurgler, 2015, Do strict capital requirements raise the cost of capital? bank regulation, capital structure and the low risk anomaly., *American Economic Review: Papers and Proceedings* 105, 315–320.

Banz, Rolf W., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3–18.

Baron, Matthew, and Wei Xiong, 2015, Credit expansion and neglected crash risk, *Working Paper, Princeton University.*

Barro, Robert, 2006a, Rare disasters and asset markets in the twentieth century, *Quarterly Journal of Economics* 121, 823–866.

——— , 2006b, Rare disasters and asset markets in the twentieth century, *Quarterly Journal of Economics* 121, 823–866.

Basu, Sanjoy, 1983, The relationship between earnings' yield, market value and return for nyse common stocks : Further evidence, *Journal of Financial Economics* 12, 129–156.

Beaver, William, Maureen McNichols, and Richard Price, 2007, Delisting returns and their effect on accounting-based market anomalies, *Journal of Accounting and Economics* 43, 341–368.

Berk, Jonathan, 1997, Does size really matter?, *Financial Analyst Journal* 53, 12–18.

Brooks, Robin, and Marco Del Negro, 2005, Country versus region effects in international stock returns, *The Journal of Portfolio Management* 31, 67–72.

Demirguc-Kunt, Asli, and Enrica Detragiache, 2002, Does deposit insurance increase banking system stability? an empirical investigation, *Journal of Monetary Economics* 49, 1373 – 1406.

Epstein, Larry, and Stan Zin, 1989, Substitution risk aversion and the temporal behavior of consumption and asset returns: A theoretical framework, *Econometrica* 57, 937–968.

Fahlenbrach, Rüdiger, Robert Prilmeier, and Renè M. Stulz, 2012, This time is the same: Using bank performance in 1998 to explain bank performance during the recent financial crisis, *The Journal of Finance* 67, 2139–2185.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of financial economics* 33, 3–56.

Frazzini, Andrea, and Lasse Heje Pedersen, 2014, Betting against beta, *Journal of Financial Economics* 1, 111–125.

Gabaix, Xavier, 2012a, Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance, *The Quarterly Journal of Economics* 127, 645–700.

——— , 2012b, Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance, *Quarterly Journal of Economics* 127, 645–700.

Gandhi, Priyank, and Hanno Lustig, 2015, Size anomalies in bank stock returns, *Journal of Finance* 70, 733–768.

GAO, U.S., 2014, Large bank holding companies: Expectations of government support, Discussion Paper, GAO-14-621.

Gorton, Gary, and Andrew Metrick, 2009, Securitized banking and the run on repo, *NBER working paper 15223.*

Gourio, Francois, 2008, Time-series predictability in the disaster model, *Finance Research Letters* 5(4), 191–203.

Harvey, Compbell R., and Akhtar Siddique, 2000, Conditional skewness in asset pricing tests, *The Journal of Finance* 55, 1263–1295.

Huang, Xin, Hao Zhou, and Haibin Zhu, 2009, A framework for assessing the systemic risk of major financial institutions, *Journal of Banking & Finance* 33, 2036 – 2049.

Kelly, Bryan, Hanno Lustig, and Stijn Van Nieuwerburgh, 2016, Too-systemic-to-fail: What option markets imply about sector-wide government guarantees, *American Economic Review* 106, 1278–1319.

La Porta, Rafael, Florencio Lopez-De-Silanes, and Andrei Shleifer, 2002, Government ownership of banks, *The Journal of Finance* 57, 265–301.

La Porta, Rafael, Florencio Lopez-de Silanes, Andrei Shleifer, and Robert Vishny, 2000, Investor protection and corporate governance, *Journal of Financial Economics* 58, 3 – 27.

Laeven, Luc, 2002, Bank risk and deposit insurance, *The World Bank Economic Review* 16, 109–137.

———, and Fabian Valencia, 2008, Systemic banking crises: A new database, *IMF Working Paper 08/224*.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, 1541–1578.

Longstaff, Francis A., and Monika Piazzesi, 2004, Corporate earnings and the equity premium, *Journal of Financial Economics* 74, 401–421.

López de Silanes, Florencio, Rafael La Porta, Andrei Shleifer, and Robert Vishny, 1998, Law and finance, *Journal of political economy* 106, 1113–1155.

O'Hara, Maureen, and Wayne Shaw, 1990, Deposit insurance and wealth effects: The value of being "too big to fail.", *Journal of Finance* 45, 1587–1600.

Panageas, Stavros, 2010, Optimal taxation in the presence of bailouts, *Journal of Monetary Economics* 57, 101–116.

Rietz, Thomas A., 1988a, The equity risk premium: A solution, *Journal of Monetary Economics* 22, 117–131.

———, 1988b, The equity risk premium: A solution, *Journal of Monetary Economics* 22, 117–131.

Romer, Christina D., and David H. Romer, 2015, New evidence on the impact of financial crises in advanced countries, *Working Paper, University of California, Berkeley.*

Wachter, Jessica, 2008, Can time-varying risk of rare disasters explain aggregate stock market volatility?, *NBER Working Papers* 14386.

Wachter, Jessica A., 2013, Can time-varying risk of rare disasters explain aggregate stock market volatility?, *The Journal of Finance* 68, 987–1035.

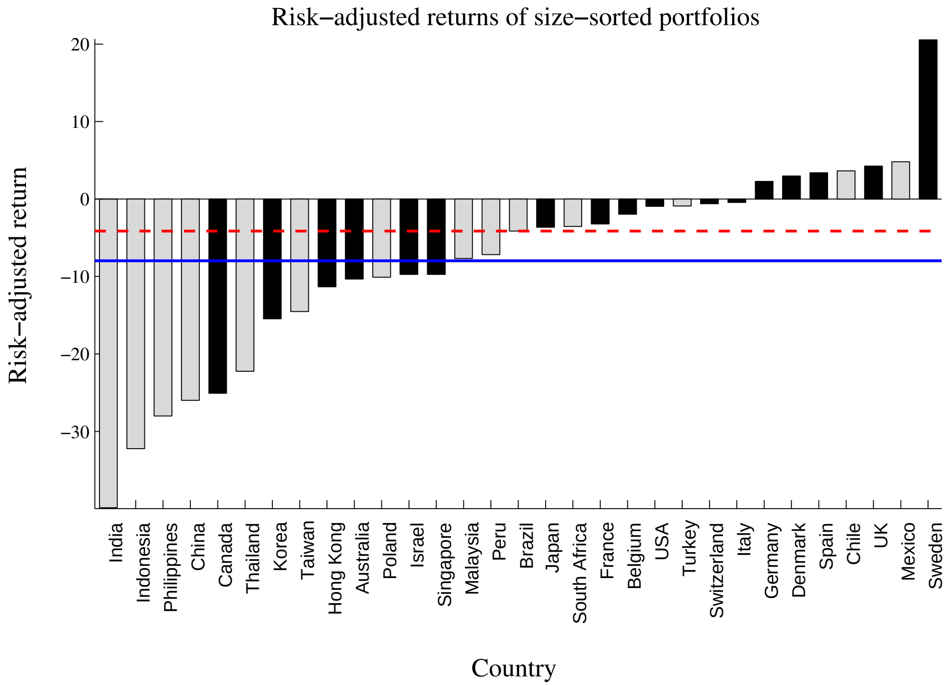

Figure 1. Average returns for size-sorted portfolios of financial firms

This figure presents the annualized mean 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 the annualized return of `Large` minus `Small`, denoted `LMS`. All returns are denominated in local currency for each country. The blue solid line presents the cross-sectional average return and the red dashed line presents the cross-sectional median return for the `LMS` portfolio. For each country, the longest available sample till 2013 is selected. Black bars denote Developed markets while white bars denote Emerging markets.

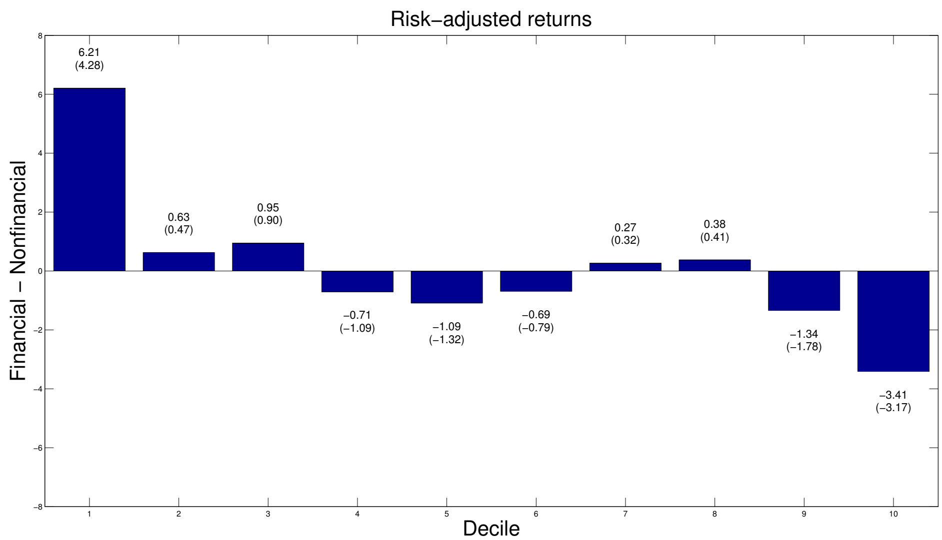

Figure 2. Risk-adjusted returns for size-sorted portfolios of financial firms vs non-financial firms for all deciles

This figure presents the risk-adjusted returns of all 10 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. We regress excess returns of the decile portfolios on the Fama and French (1993) risk factors. Figures in parenthesis are t-statistics. For each country, the longest available sample till 2013 is selected.

Table 1. Summary statistics for financial firms by country

Notes: This table presents summary statistics for the financial firms in our sample, by country. `N` is the number of distinct financial firms, `%N` is the average percentage of all publicly listed firms classified as financial firms, and `%Mcap` is the average market capitalization of financial firms as a percentage of total market capitalization of all publicly listed firms. For each country, the longest available sample till 2013 is selected. `Year` indicates the starting year.

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

Table 2. Summary statistics for size-sorted portfolios of financial firms

Notes: This table presents 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, and `LMS` denotes the monthly return of `Large` minus `Small`. For the `Large` and `Small` portfolios we report: `N`, the number of distinct financial firms; `Fcap`, the average market capitalization as a percentage of the market capitalization of the entire financial intermediary sector; `%Turn`, the turnover ratio, computed as the probability (in %) that a firm migrates to another portfolio in the subsequent month; `Ret`, the average value-weighted monthly return. For `LMS`, we report the average monthly return (`Ret`) and its *t*-statistic based on standard errors clustered by time and country. The statistics are averaged across countries, across Developed markets only, and across Emerging markets only. 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 till 2013 is selected.

	`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 3. Risk adjusted returns for size-sorted portfolios of financial firms and non-financial firms

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 the abnormal 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 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 till 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 4. Risk adjusted returns for size-sorted portfolios of financial firms over time

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 the abnormal 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, Large financial firms are matched to Small financial firms in the same `SMB` decile. In Panel C, Large financial firms are matched to Small financial firms in the same `Market` decile. In Panel D, Large financial firms are matched to Small financial firms with closest Idiosyncratic Volatility. In Panel E, 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.

	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: 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 C: 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 D: 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
Panel E: 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 5. 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 abnormal 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.

	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 6. 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 the abnormal return (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. 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.

	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 7. 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 8. 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 the value 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, while 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 till 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 9. Legal 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' 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 5-year non-overlapping windows, $t+1$ to $t+5$. The dependent variable is the estimated abnormal return on `LMS` for country j. The regressors are: *Legal*, a dummy variable that equals 1 if country j follows common law; *Governance* and *Creditor*, the corporate governance and disclosure indices from La Porta, Lopez-de Silanes, Shleifer, and Vishny (2000) and López de Silanes, La Porta, Shleifer, and Vishny (1998), respectively. TFE indicates time fixed-effects. Each column represents 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. Columns 1-4 refer to all financial firms, while columns 5-8 are for Banks and Financial Services firms only. For each country, the longest available sample till 2013 is selected.

	`Fin`				`Banks and Fin Serv.`			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Legal	-8.52***			-13.99***	-2.56			-8.15**
	(-3.23)			(-4.66)	(-0.68)			(-2.02)
Governance		2.96**		5.88***		5.59***		6.16**
		(2.51)		(4.14)		(3.05)		(2.57)
Creditor			-0.30	-0.26			4.03**	1.72
			(-0.26)	(-0.19)			(2.30)	(0.88)
TFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	154	144	154	144	104	99	103	99
R^2	0.12	0.08	0.05	0.24	0.04	0.13	0.08	0.17

Table 10. Financial 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' 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 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 over 5-year non-overlapping windows, $t+1$ to $t+5$. The dependent variable is the estimated abnormal return on `LMS` for country j. The regressors are: `Deposit`, a dummy variable that equals 1 if country j has bank deposit insurance; `Borrow`, the percentage of population that has borrowed from a bank; `Bank Credit/GDP`, the ratio of bank credit to GDP; `Developed`, a dummy variable that equals 1 if country j is classified as a developed market. TFE and CFE represent time and country fixed-effects, respectively. Each column represents 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. Columns 1-4 refer to all financial firms, while columns 5-8 are for Banks and Financial Services firms only. For each country, the longest available sample till 2013 is selected.

	`Fin`				`Banks and Fin Serv.`			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deposit	3.23			1.87	-9.50**			-10.23**
	(1.13)			(0.59)	(-2.15)			(-2.08)
Borrow		-2.83**		-2.58*		-2.18		-1.92
		(-2.09)		(-1.85)		(-1.23)		(-1.00)
Bank Credit/GDP			-8.02***	0.42			-3.66	4.81***
			(-2.86)	(0.34)			(-1.20)	(2.96)
Developed		7.27**		7.08**		0.14		-0.94
		(2.57)		(2.13)		(0.03)		(-0.19)
TFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CFE	No	No	Yes	No	No	No	Yes	No
N	154	149	147	142	104	102	98	96
R^2	0.05	0.10	0.60	0.11	0.08	0.06	0.67	0.17

Table 11. Sovereign finances 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' sovereign finances. 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 returns to 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 5-year non-overlapping windows, $t+1$ to $t+5$. The dependent variable is the estimated abnormal return on `LMS` for country j. The regressors are: `Surplus`, the budget surplus or deficit; `Spread`, the spread on the long-term sovereign bond in excess of the U.S. one; `Currency`, a dummy variables that equals 1 if there is a currency crisis in country j. TFE and CFE represent time and country fixed-effects, respectively. Each column represents 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. Columns 1-4 refer to all financial firms, while columns 5-8 are for Banks and Financial Services firms only. For each country, the longest available sample till 2013 is selected.

	`Fin`				`Banks and Fin Serv.`			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Surplus	-3.75***			-3.88**	1.05			1.26
	(-2.78)			(-2.52)	(0.39)			(0.41)
Spread		3.82*		1.82		-3.45		-0.95
		(1.67)		(0.61)		(-1.03)		(-0.22)
Currency			-15.99***	-6.37			-21.16***	-3.71
			(-2.97)	(-1.02)			(-3.03)	(-0.88)
TFE	Yes	No	Yes	No	Yes	No	Yes	No
CFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	105	133	154	98	83	95	104	79

Table 12. Policy responses 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' policy responses to a crisis.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 returns to portfolios of firms with the highest and lowest market capitalization. We regress the difference in the return to `Large` minus `Small`, denoted `LMS`, on the Fama and French (1993) risk factors over 3-year non-overlapping windows, $t+1$ to $t+3$. The dependent variable is the estimated abnormal return on `LMS` for country j. The regressors are: `Bank`, a dummy variable that equals if the country has experienced a banking crisis in the past 3-year period; `Nationalize`, `AssetPurchase`, which measure the regulatory responses to banking crisis, and are interacted with `Bank`; `Surplus`, the ratio of budget surplus or deficit to GDP; `Support`, the cost of support to the banking system, which is interacted with `Surplus`. TFE and CFE represent time and country fixed-effects, respectively. All variables are standardized. Each column represents 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. Columns 1-4 refer to all financial firms, while columns 5-8 are for Banks and Financial Services firms only. For each country, the longest available sample till 2013 is selected.

	`Fin`				`Banks and Fin Serv.`			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank	-1.87	-3.76	4.11		-8.85	0.87	1.64	
	(-0.47)	(-0.93)	(0.46)		(-1.12)	(0.12)	(0.07)	
Nationalize × *Bank*	-12.64*				-0.28			
	(-1.86)				(-0.03)			
AssetPurchase × *Bank*		-1.07				-13.06		
		(-1.44)				(-1.40)		
Combined × *Bank*			-3.58				-2.37	
			(-1.32)				(-0.43)	
Surplus				-1.43				1.16
				(-0.63)				(0.37)
Support × *Surplus*				-2.02				-15.62*
				(-0.40)				(-1.91)
TFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	153	153	153	121	102	102	102	87
R^2	0.44	0.44	0.44	0.41	0.45	0.46	0.45	0.42

Table 13. 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 abnormal 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 the groups of Developed and Emerging markets. Panel C reports the average subsidy across geographical regions.

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