Option-Based Intermediary Leverage*

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Abstract

We introduce an option-implied proxy for the health of financial intermediaries—the Leverage Bearing Capacity (LBC). LBC is the leverage of a fictitious intermediary that targets a fixed level of risk and rebalances its capital structure on an ongoing basis. Our measure is based on market values, available at any frequency, and naturally incorporates higher moments. We analyze the dynamics of LBC within simulation and event studies and demonstrate that LBC is tightly linked to financial sector uncertainty. Building on an intermediary asset pricing model, we validate that LBC proxies the marginal wealth of intermediaries. Empirically, LBC explains the expected returns across several asset classes and subsumes the explanatory power of existing measures of intermediaries' health, financial uncertainty, and common risk factors.

Keywords: Intermediary asset pricing, financial intermediation, option-implied information, leverage, financial constraints, risk-bearing capacity, balance sheet valuation

JEL: G12, G13, G20, G32

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1 Introduction

Not only since the global financial crisis, financial intermediaries (FIs) have a place in the spotlight of asset pricing. There is an ongoing debate whether intermediaries are marginal price setter (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014) or just a 'veil' (Santos and Veronesi, 2021). The answer to this question is notoriously difficult to find because of the lack of an adequate instrument. The consumption of intermediary managers—the theoretical ingredient for intermediary asset pricing tests in many models—is not observable. Therefore, most empirical studies use some measure of leverage to proxy the health of FIs (He, Kelly, and Manela, 2017; Adrian, Etula, and Muir, 2014). While this choice is theoretically justified, empirical leverage ratios are based on book values of debt because corporate bonds are illiquid, noisy, and not all assets of bond-issuing companies have observable market values (Culp, Nozawa, and Veronesi, 2018). In this paper, we use option prices to obtain a measure of intermediary health that is completely based on market valuation, available at any frequency, and inherently reflects higher moments and risk preferences.

The reliance on book values of debt in empirical intermediary asset pricing gives rise to some concerns. First, book values are historical information and depend on country-specific accounting standards. Especially when assets are not easy to liquidate, accounting values do not fully reflect the actual marketable value. Second, book values are published quarterly. The proposed measures for intermediary asset pricing are only available at a low frequency and, hence, inadequate for studying the influence of specific events. Third, and most importantly, book values do not fully incorporate higher-moment risk (e.g., uncertainty), although it has first-order importance for the real economy (Bloom, 2009), asset prices (Bekaert, Engstrom, and Xing, 2009), and actual intermediaries' balance sheet operations (Adrian and Shin, 2010).[1] Market values capture the intermediaries' ability to raise capital and, hence, reflect the financial health of the intermediary sector. Accordingly, market-based measures of intermediaries' health are necessary to study the impact of FIs on asset prices.

To obtain a market-based measure of intermediary health that overcomes the shortfalls of book values, we apply the concept of 'pseudo firms', an idea recently introduced by Culp, Nozawa, and Veronesi (2018). The central insight of this framework is that a market-based assessment of any company's balance sheets can be extracted from option prices. The only necessary assumption is

[1]Adrian and Shin (2010) show that intermediaries actively manage their balance sheet in response to changes in the first moment (level) but also the second moment (uncertainty) of their assets.

the absence of arbitrage. We use this idea and construct pseudo financial intermediaries (pseudo-FIs) based on real NY Fed Primary Dealers to compute their Leverage Bearing Capacity (LBC). LBC is the fictitious leverage of a pseudo-FI that targets a fixed level of risk and, therefore, rebalances its capital structure on an ongoing basis. Thus, LBC inherently gauges the active capital structure adjustments of intermediaries that operate according to the VaR rule, which states that intermediary equity has to cover the Value-at-Risk (Adrian and Shin, 2010, 2014).

Capital structure adjustments are the result of changes in prices and uncertainty. Negative shocks to the intermediaries' equity lead to fire-sales to reduce the VaR. A positive shock to uncertainty has a similar effect. To understand how LBC reacts to price and uncertainty shocks, we simulate different scenarios using the stochastic volatility model of Heston (1993). LBC decreases if stock prices drop because uncertainty increases due to the leverage effect. Equity and debt lose value simultaneously, so the pseudo-FI restructures its balance sheet and can bear less leverage for the same level of risk. A positive shock to uncertainty lowers LBC instantaneously due to higher default risk. The effect is further enhanced as the pseudo-FI has to rebalance its book debt to attain the desired level of risk.

To examine the effect of real-world shocks, we conduct event studies during the financial crisis in 2008 and the stock market rally in 2016. We compare the dynamics of LBC to the measure of He, Kelly, and Manela (2017, hereafter HKM) over a short window of time in which book values of debt did not change. During the financial crisis, we document that LBC and the measure by HKM react similarly. However, as LBC incorporates uncertainty directly, its reactions are amplified whenever aggregate uncertainty (e.g., VIX) spikes or drops. Next, we show that LBC and the measure by HKM behave differently during the stock market rally in 2016. While the latter increases steadily, LBC drops considerably at the beginning of the rally. The divergence is attributable to an increase in financial sector-specific uncertainty. LBC captures changes in market values of equity and debt, while book debt is artificially fixed over the observation period in the measure of HKM. To examine which measure more accurately gauges the health of intermediaries, we classify asset returns into more and less intermediated (Haddad and Muir, 2020). The returns of more intermediated asset classes earn negative returns after the election and thus confirm the reaction of LBC in that financial intermediaries are more constrained around that time.

We then turn to the asset pricing implications of LBC. Building on the canonical model of He and Krishnamurthy (2013), we show that LBC is a theoretically valid proxy for the marginal utility of intermediaries. LBC is pro-cyclical and negatively correlated with the marginal value of intermediary wealth. Hence, we expect a positive market price of risk for LBC in our empirical asset pricing tests. We estimate the market price of risk for LBC across seven major asset classes and a pooled portfolio consisting of all assets. LBC explains the cross-sectional return differences of several portfolios significantly. The market prices of risk are positive and thus in line with theoretical predictions. We highlight that the pricing performance of LBC outperforms conventional measures of intermediary health. Specifically, LBC is not only priced in more asset classes, but it also subsumes the pricing power when we conduct horse races. Standard risk factor models (i.e., the Fama-French five-factor model) do not span our intermediary risk factor. Our results are robust to various calibration choices, alternative test portfolios, and sub-periods. Lastly, we focus on the uncertainty dimension concerning the empirical pricing performance. Our results show that the pricing power of the measure of HKM disappears when uncertainty is included. LBC, however, subsumes the measure of HKM as well as uncertainty in joint asset pricing tests. Hence, LBC contains additional information about intermediary constraints compared to a combination of HKM and uncertainty.

All in all, our option-implied proxy measures the health of the intermediary sector and improves upon existing measures. This improvement is because LBC is completely based on market values, inherently captures the uncertainty dimension, and complies with actual FI capital structure adjustments.

Related Literature To test if intermediaries are marginal price setters, earlier work by HKM and Adrian, Etula, and Muir (2014) has focused on Euler equation tests for different asset classes. Both studies propose intermediary leverage as a factor driving asset returns but differ in the construction of their measures. While Adrian, Etula, and Muir (2014) use the quarterly Flow of Funds to construct intermediary leverage based on book values, HKM use market equity of intermediaries and book value of debt from quarterly balance sheets. In contrast, we construct a measure of intermediaries' health that is solely based on market values and available at any frequency.

Santos and Veronesi (2021) argue that only time-varying risk aversion of households drives intermediary leverage and asset prices. In their model, intermediaries are a veil and invest on behalf of the household. Hence, successful tests of intermediaries' Euler equation are a necessary but not sufficient condition to show that intermediaries matter for asset prices (He and Krishnamurthy, 2018). Additionally, the Euler equation of the constrained household must not hold for intermediated assets. Empirically, Haddad and Muir (2020) rank asset classes by their degree of intermediation and show that more intermediated assets are more predictable by intermediary measures. However, they use the average of the measures by Adrian, Etula, and Muir (2014) and

HKM as a predictor, forcing them to use a quarterly horizon. We add to this discussion by providing a measure that allows the identification of shocks to intermediary health over short periods. This helps to distinguish shocks to intermediaries' health from changes in household risk aversion.

Dahlquist, Sokolovski, and Sverdrup (2021) show that intermediaries matter for the cross-section of hedge fund returns. Hedge funds with a higher exposure to systematic intermediary risk have higher expected returns after controlling for common risk factors. Chen, Joslin, and Ni (2019) propose a proxy based on deep out-of-the-money put option demand. They interpret a heightened demand by intermediaries for deep out-of-the-money put options as a tightening of intermediary constraints. In contrast, we build our measure on the full continuum of option prices to link them to the capital structure of financial intermediaries.

Du, Tepper, and Verdelhan (2018) use an event study approach on covered interest parity (CIP) violations after the financial crisis as an identification strategy. They directly link these violations to regulatory constraints becoming binding on specific dates (quarter-end) without other relevant information becoming public. Du, Hebert, and Wang (2020) build on this idea and propose the size of CIP violations as an additionally priced factor. Similar to LBC, their "forward CIP trading strategy" factor is available at any frequency. We mainly differ from Du, Hebert, and Wang (2020) in that we do not propose LBC as an additional factor to intermediary leverage. Rather, we add to the literature by proposing a more precise measure for the health of intermediaries. Hence, Du, Hebert, and Wang (2020) and LBC can be seen as two complementary factors. As both are available at a daily frequency, the use of LBC instead of the measure proposed by HKM allows better identification of the sources of the CIP violations.

2 Leverage Bearing Capacity

2.1 Pseudo Financial Intermediaries

We build our measure of intermediary risk on the *insight* of Merton (1974) that options written on firms' total assets replicate the financial claims of the respective equity- and debt holders.[2] In this line, Culp, Nozawa, and Veronesi (2018) introduce the idea of 'pseudo firms' in the context of credit risk. The authors build fictitious firms with assets comprised of traded securities, that is, the stock

[2]We refer to the *basic insight* of Merton (1974) while we explicitly do not build on the credit risk model introduced in the same paper.

of a genuine firm. The 'pseudo firms' are financed by equity and zero-coupon bonds. Culp, Nozawa, and Veronesi (2018) show that the time-series properties of bonds issued by pseudo firms are similar to actual corporate bonds while circumventing typical empirical issues that usually arise in the bond market. The framework is simple, relies solely on no-arbitrage, and allows us to construct fully observable balance sheets. We apply this approach and create fictitious financial intermediaries with simple balance sheets extracted from traded securities. In contrast to Culp, Nozawa, and Veronesi (2018), we only focus on financial intermediaries and do not make assumptions about underlying asset return dynamics.[3]

Consider an intermediary i that finances its total assets A with equity E and debt D. For simplicity, we assume that the intermediary issues a zero-coupon bond with face value K^i, which must be repaid at maturity date T.[4] On that date, the intermediary either meets its debt obligations ($A^i_T \geq K^i$) or files for bankruptcy ($A^i_T < K^i$). In case of no default, debt holders receive the face value K^i while shareholders earn the residual total asset value after repaying the book debt, $A^i_T - K^i$. If total assets do not suffice to repay debt at maturity, the firm defaults and creditors take over the firm due to the seniority of debt. All remaining assets, A^i_T, are distributed among creditors while shareholders lose their entire capital.

The payoff for shareholders at T is thus equal to $\max\{A^i_T - K^i, 0\}$, which is precisely the payoff of a European call option C written on the total assets of the firm. For debt holders, the payoff is $K^i - \max\{K^i - A^i_T, 0\}$, which equals the value of a default-free bond K^i minus the market value of a put option on the traded securities with strike K^i. In the absence of arbitrage, the time-t market values of equity E^i_t and debt D^i_t for firm i are thus equal to

$$E^i_t = C(A^i_t, K^i, \tau^i), \tag{1}$$

$$D^i_t = Z_{t,\tau^i} K^i - P(A^i_t, K^i, \tau^i), \tag{2}$$

where Z_{t,τ^i} is the price of a risk-free zero-coupon bond with time to maturity $\tau^i = T^i - t$. The payoffs of shareholders and debt holders differ mainly with respect to their directional risk. The shareholders have unlimited upside potential and do not participate in losses below the nominal book debt. The debt holders, on the other hand, carry the risk that the asset value deteriorates further below the book debt and consequently bear the downside risks of the assets. Hence, an increase of uncertainty symmetrically affects downside risk as well as upside potential and, thus,

[3]Culp, Nozawa, and Veronesi (2018) assign credit ratings based on historical asset returns and exogenous return dynamics.

[4]Precisely, the maturity date T is just the instant before the firm repays its debt.

leads to a higher equity value and lower market value of debt. Focusing exclusively on book debt neglects the downside risks inherently captured in the market valuation of debt.

Overall, the above insights allow us to assess the balance sheet of that firm at any given time before maturity as long as prices for options written on the firms' total assets are empirically observable. However, while stock prices can be reinterpreted as call options written on total assets, corresponding put options do not trade in the market. Therefore, we follow Culp, Nozawa, and Veronesi (2018) and construct pseudo-FIs in which total assets only comprise the stock price S^i of the actual financial intermediary i. Figure 1 presents the market valuation of their balance sheets at time t.

Figure 1: Pseudo Financial Intermediaries' Balance Sheet in Market Values

Pseudo Financial Intermediary i

Assets	Liabilities
S_t^i	$D_t^i = Z_{t,\tau^i} K_t^i - P(S_t^i, K_t^i, \tau^i)$
	$E_t^i = C(S_t^i, K_t^i, \tau^i)$

Given the book debt K_t^i and its time to maturity τ^i, the real firm stock price S_t^i, the risk-free discount factor Z_{t,τ^i}, the European option prices $C(S_t^i, K_t^i, \tau^i)$ and $P(S_t^i, K_t^i, \tau^i)$ constitute a fully observable balance sheet for each pseudo-FI i, available at almost any frequency. This approach only relies on no-arbitrage conditions such that each pseudo-FI can be treated as a firm that is tightly linked to its real counterpart.[5] The strong connection between an actual and a pseudo firm follows from the underlying return distribution of the stock price. Since the equity of the true FI is levered itself, changes in the leverage of the intermediary enter the return distribution of the stock and, therefore, the balance sheet of the pseudo-FI.

[5]Theoretically, one can construct infinite pseudo-FI by varying the choice of outstanding debt as well as debt maturity.

2.2 Intermediary Risk Factor

Using the fully observable balance sheet, we define the leverage ratio of each pseudo financial intermediary to be our intermediary risk factor. To make pseudo financial intermediaries comparable, we have to fix two target parameters. First, we set the debt maturity to a fixed value of τ^* across all intermediaries to control for term structure effects. Economically, a constant debt maturity corresponds to a pseudo-FI that refinances its current debt at the beginning of each point in time by issuing new debt with maturity τ^*. Second, each pseudo-FI needs to follow a joint debt policy to avoid arbitrary choices of book debt K. To do so, we build pseudo-FIs which always re-balance their capital structure to keep their relative expected loss constant. A constant expected loss ratio is closely related to the concept of intermediaries targeting fixed value-at-risks (Adrian and Shin, 2014). We define the discounted relative expected loss ratio REL^i of the pseudo-FI i as

$$REL_t^i = \frac{P(S_t^i, K_t^i, \tau^*)}{K_t^i}, \tag{3}$$

which is the ratio of the discounted expected loss $P(\bullet)$ relative to one unit outstanding book debt K_t^i. This ratio is closely related to the economic VaR introduced by Aït-Sahalia and Lo (1998). It incorporates the expected loss, the probability of default, and the economic valuation of the respective states. We set this ratio to a constant value of REL^* to ensure that each pseudo-FI targets the same expected loss ratio over time. That is, we search for the pseudo-FI with exactly our targeted REL^* by setting book debt to $K_t^{i,*}$. Hence, the choice of book debt follows endogenously from the discount each pseudo-FI pays for its individual risk.

We then calculate our proposed measure—the Leverage Bearing Capacity LBC_t^i—as the leverage of the pseudo-FI i:

$$LBC_t^i = \frac{D_t^i}{E_t^i} = \frac{Z_t K_t^{i,*} - P(S_t^i, K_t^{i,*}, \tau^*)}{C(S_t^i, K_t^{i,*}, \tau^*)}. \tag{4}$$

Each pseudo-FI pursuing a debt policy with constant debt maturity τ^* and relative expected loss ratios REL^* has to set its book debt K so that its leverage equals LBC_t^i.

An increase in LBC_t^i indicates that the *pseudo*-FI can increase its leverage without changing its expected loss. Naturally, the *true* market leverage of financial intermediaries does not match LBC in absolute terms. However, changes in the marginal value of wealth enter LBC accordingly, implying that the change of LBC is a reliable proxy of the intermediary pricing kernel. To test its relevance for asset pricing, we define ψ as the value-weighted change in LBC of each pseudo-FI

Figure 2: Leverage Bearing Capacity

This figure depicts the cumulative monthly log change of LBC over the whole sample period from 1996 to 2019 for a target maturity of $\tau^* = 150$ days and an expected loss ratio of $REL^* = 8\%$.

such that

$$\psi_t = \sum_{i=1}^{n} w_{t-1}^i \left[\log\left(LBC_t^i\right) - \log\left(LBC_{t-1}^i\right) \right], \tag{5}$$

where w is the market share of the true FI i measured by its market capitalization at time t.

Figure 2 plots the cumulated log change of LBC for a target maturity of $\tau^* = 150$ days and an expected loss ratio of $REL^* = 8\%$. LBC drops sharply in the hedge fund crisis of 1998, the Great Recession in 2008, and the European Debt Crisis in 2012 since these are times where financial intermediaries face severe capital constraints. The dot-com bubble in 2002 and the Chinese stock market sell-off in 2015 do not affect the Leverage Bearing Capacity of financial intermediaries to a large extent. As these crises originated in less intermediated asset classes, LBC accordingly captures only minor effects on the balance sheet of financial intermediaries. The time-series properties of LBC are thus intuitively in line with the idea of intermediary asset pricing.

2.3 Why Does LBC Change over Time?

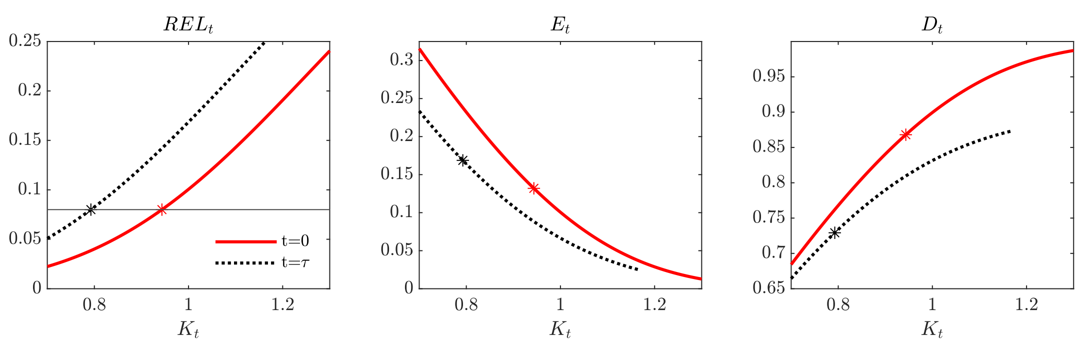
In this section, we investigate how shocks to the stock price and uncertainty affect LBC over time. For the sake of simplicity, we use artificial option prices based on the model by Heston (1993). In this framework, the stock price S_t is the value of the pseudo-FI's assets and has time-varying volatility V_t. The dynamics are given by

$$\frac{dS_t}{S_t} = rdt + \sqrt{V_t}dW_S, \tag{6}$$

$$dV_t = \kappa(\theta - V_t) + \sigma_V(\rho dW_S + \sqrt{1-\rho^2}dW_V). \tag{7}$$

We use a calibration with $r = 0$, $\kappa = 2.7220$, $\theta = 0.1346$, $\sigma = 0.5881$, and $\rho = -0.7172$. The leverage effect, i.e., the negative correlation of the Brownian motions dW_S and dW_V, induces a higher (lower) level of volatility if negative (positive) shocks to the stock price realize. We set $S_0 = 1$ and $V_0 = \theta$ to compute prices of put and call options with strikes K_t from 0.7 to 1.3. Based on these option prices, we determine LBC as the leverage ratio of a pseudo-FI with a fixed level of REL of 0.08 and τ of 150 days. Subsequently, we impose a one standard deviation shock to the stock price and volatility in separate scenarios.

Figure 3: Stock Price Shock

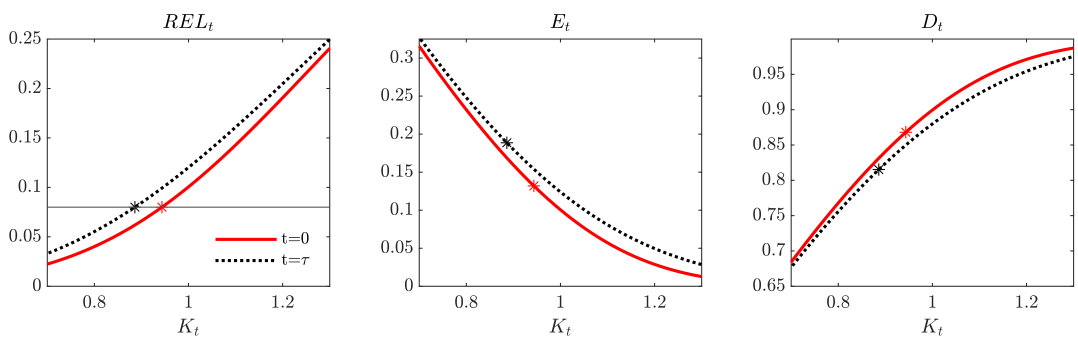


This figure depicts model-implied values of market equity E_t, market debt D_t, and the relative expected loss REL_t across different strike prices K_t for a fictitious pseudo-FI. The solid, red line denotes the initial values and the dotted, black line the values after a one standard deviation stock price shock dW_S. The stars denote the respective values used for the calculation of LBC resulting in an REL of 0.08 and a τ of 150 days.

Figures 3 and 4 present the relative expected loss REL_t, the market value of equity E_t, and the market value of debt D_t for different levels of book debt. The solid red (dotted black) line shows possible values of REL_t, E_t, and D_t before (after) the realization of the shocks. We mark the values that we use in the calculation of LBC with a star. At t = 0, the pseudo-FI with a REL_0 of 0.08 has a book value of debt $K_0 = 0.944$. The initial market value of debt D_0 is 0.868 and the initial market value of equity E_0 is 0.132. Hence, its leverage ratio $\frac{D_0}{E_0}$ is 6.58.

In Figure 3, we impose a negative one standard deviation shock in S_t. Due to the negative correlation of stock prices and volatility, uncertainty increases as well. We observe that REL_τ rises from 0.08 to 0.14 before the rebalancing as the asset value decreases and debt becomes riskier. The market value of equity falls from 0.132 to 0.088, while the market value of debt falls to 0.810. That is, the market value of debt reacts more strongly to the shock than the market value of equity, resulting in a leverage ratio of 9.16 for the pseudo-FI. The new pseudo-FI, however, targets a REL of 0.08 again and thus only issues debt with a face value K_τ of 0.7926. The corresponding market value of debt is 0.7292, while equity has a market value of 0.1687. The leverage ratio is merely 4.32 as a result of this. In a world without the leverage effect, both effects—the drop in the stock price and the deleveraging—would cancel out, and LBC would not change.[6] With the leverage effect, the rebalancing effect dominates the stock price shock due to the heightened uncertainty. To summarize, the pseudo-FI at $t = \tau$ can only bear a leverage of 4.32 for the same risk, whereas the pseudo-FI at $t = 0$ could take up a leverage of 6.58. As a result, the change in LBC ψ_τ is negative (-0.42), indicating that the pseudo-FI is in a worse state.

Figure 4: Uncertainty Shock



This figure depicts model-implied values of market equity E_t, market debt D_t, and the relative expected loss REL_t across different strike prices K_t for a fictitious pseudo-FI. The solid, red line denotes the initial values and the dotted, black line the values after a one standard deviation uncertainty shock dW_V. The stars denote the respective values used for the calculation of LBC resulting in an REL of 0.08 and a τ of 150 days.

In the second scenario, depicted in Figure 4, uncertainty increases by one standard deviation. The relative expected loss increases to 0.1058 due to higher default risk, which translates to a lower market value of debt (0.8437). Equity, on the other hand, increases to 0.1601 due to its asymmetric payoff profile and the higher upside potential. LBC instantaneously drops to 5.27 as a reaction to the uncertainty shock. To reduce its REL to the desired level of 0.08, the pseudo-FI issues total debt with a face value of only $K_\tau = 0.8667$. The corresponding market value of debt is D_τ is 0.7974 while the market value of equity E_τ is 0.2065. As both effects—the uncertainty shock and

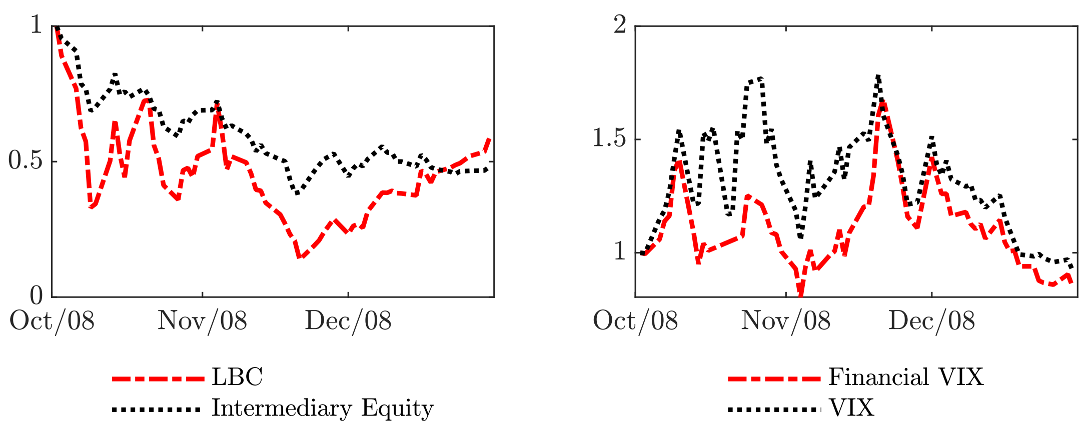
[6]We test this by setting the correlation ρ to zero. In this case, LBC does not react to stock price changes.

the rebalancing effect—go in the same direction, LBC drops to only 3.86, that is $\psi_\tau = -0.53$.

2.4 LBC in the Wild: The Effect of Uncertainty

To examine how LBC and intermediary equity react to actual asset and uncertainty shocks, we analyze two real-world examples. In general, intermediary equity is closely linked to the measure used by He, Kelly, and Manela (2017) as the book debt does not change over the observed period. In Figure 5, we plot the dynamics of LBC, intermediary equity, and uncertainty during the financial crisis. All time series are normalized and start with a value of one on Oct. 1, 2008. As is evident, LBC and intermediary equity sink drastically over the first two weeks, but the reaction of LBC is largely amplified. This is because LBC captures the sharp increase in uncertainty, as indicated by the elevated VIX and Financial VIX.[7] The interventions of the US government and the Fed in December 2008 resolve uncertainty and cause a steady recovery of LBC. Intermediary equity, in contrast, is hardly affected by the resolution of uncertainty and remains almost unchanged. Overall, we see that both measures reacted similarly during the financial crisis, but LBC reacts more amplified as it incorporates changes in uncertainty.

Figure 5: LBC during the Financial Crisis



This figure depicts LBC (dashed) and the value-weighted intermediary equity (dotted) for the period from Oct. 1, 2008, to Dec. 31, 2008. We normalize both time series by their level on Oct. 1, 2008. Note that four observations are missing from Oct. 17th to Oct. 22nd due to data availability.

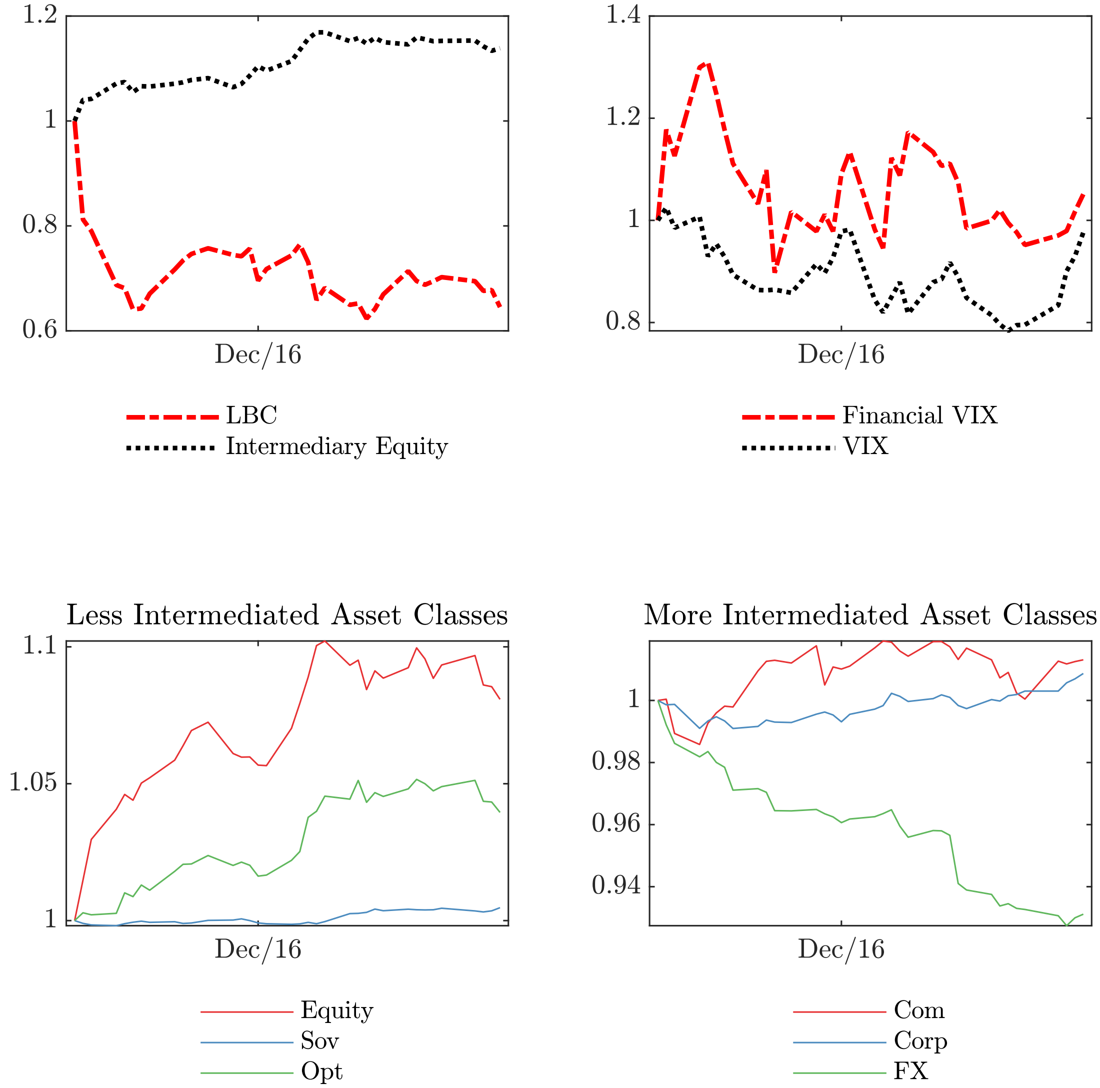
[7] We measure uncertainty in the financial sector by applying the VIX formula to options on the Financial SPDR index used by Kelly, Lustig, and Van Nieuwerburgh (2016). The correlation of the VIX and financial VIX over the whole time series is 91%.

Next, we consider a non-obvious example where LBC dropped—the election of Donald Trump as the 45^{th} President of the United States of America on November 8, 2016. The stock market rallied during the rest of the year 2016 and the financial sector performed particularly well in expectation of the coming deregulations (Wagner, Zeckhauser, and Ziegler, 2018). The top left panel of Figure 6 confirms this and shows that intermediary equity steadily increased after Trump's election. LBC, however, decreased by more than 40%, indicating that intermediaries were more constrained. Although puzzling at first glance, the reaction of LBC to Trump's election makes sense if we take uncertainty into account. Overall uncertainty—measured by the VIX—was not heightened after the election but instead decreased.[8] The uncertainty in the financial sector, however, increased strongly, as shown in the top right panel of Figure 6. Although the election of Trump led to higher valuations of intermediaries, it also increased the riskiness of the assets held by the intermediaries. The latter effect dominated the increase in equity, leading to an overall decline in LBC.

These examples show that intermediary equity and LBC react similarly to shocks but can also diverge. Of course, the divergence will only be good news if LBC reflects the health of the intermediary sector better. To test this, we follow Haddad and Muir (2020) and classify asset returns into less and more intermediated asset classes. The less intermediated asset classes consist of equity, sovereign, and options while the more intermediated classes consist of commodity, corporate bonds, and FX. We plot the average returns for the asset classes in the bottom left and right plot of Figure 6. The less intermediated assets tend to follow a steady upward trend. In contrast, the more intermediated class exhibits more erratic dynamics. We observe short-lived downward moves in all three assets, which coincide with the drop in LBC. Corporate bonds and commodities recover, and so does LBC. Hence, the dynamics of LBC are largely in line with the behavior of more intermediated asset returns. While this anecdotal evidence shows that LBC incorporates information not included in intermediary equity, the question remains whether LBC is consistently better at explaining asset prices than intermediary leverage. We answer this in Section 4.

[8]VIX futures increased immediately after the election but came down within a few hours after the conciliatory speech of Trump.

Figure 6: The “Trump Rally”



The top left plot depicts LBC (dashed) and the value-weighted intermediary equity (dotted). The top right plot shows the Financial VIX (dashed) and the VIX (dotted). In the bottom left plot, we show the cumulative return of less intermediated asset classes (Equity, Sovereign Bonds, Options). In the bottom right plot, we show the cumulative return of more intermediated asset classes (Commodities, Corporate Bonds, FX). The return for each asset class is calculated as the average across all test portfolios. We describe the portfolios in A. We do not include CDS because of the lack of daily data. We normalize every time series by their level on Nov. 8, 2008. All plots show the period from the election day of Trump, Nov. 8, 2016, until Dec. 31, 2016.

3 Empirical Implementation

3.1 Intermediary Universe and Options

We follow He, Kelly, and Manela (2017) and include all New York Fed primary dealers to our intermediary universe. New York Fed primary dealers are large intermediaries that are expected to serve as counterparties for open market operations, one of the primary instruments for the transmission of monetary policy. Several criteria must be fulfilled to be eligible as a primary dealer. Most importantly, the financial intermediary must be either a broker-dealer with at least USD 50 million in net regulatory capital or a supervised bank with a minimum of USD 1 trillion Tier 1 capital. Thus, the list consists of the largest and most relevant intermediaries such as J.P. Morgan, BofA, or Wells Fargo. In contrast to Adrian, Etula, and Muir (2014), who use subsidiary level data (Flow of Funds), the use of primary dealers ensures that the intermediary's health is measured at the holding company level.[9]

Effectively, the sample of intermediaries is dictated by the construction of our measure, relying on the availability of option data. Therefore, we have to exclude dealers that are not listed or for which no options are available at the IvyDB US options database.[10] The data availability also sets the start date of our analysis to January 1996. Table A.1 provides a detailed overview of all primary dealers we use. As the table shows, all major intermediaries are part of our sample. We use CUSIPs to match option data with stock prices provided by CRSP. We filter out options with a negative time value, zero bid or ask price, unreasonable bid-ask spread ($\frac{bid}{ask} > 15$), zero open interest, and maturity of fewer than seven days. Furthermore, we delete all options that come with a quoted future price of -99.99. The future prices indicate that a merger or similar stock price events have previously been announced, yet the options are still quoted until the end of maturity.

Table 1 provides summary statistics about the filtered option data. We calculate the daily average number of options, open interest, and volume per bank for four different sub-samples and moneyness buckets and take the median across banks.[11] As is evident in the summary statistics, options data are liquid throughout our sample. For all sub-periods, the average number of strikes per moneyness bucket is larger than four. Open interest and daily trading volumes are also reasonably

[9] See the in-depth discussion in He, Kelly, and Manela (2017).

[10] These banks are mostly non-US banks such as BNP Paribas or Societe Generale.

[11] Note that taking the median across the panel of banks is more conservative than calculating a daily average across all banks. This is because options on large banks such as JPM inflated the numbers if we would use one large time series.

Table 1: Option Data Summary Statistics

	1996-2000	2001-2007	2008-2012	2013-2019
Moneyness (m)	*Panel A: Daily Number of Options*			
$0.90 \leq m < 0.95$	4.14	4.46	4.86	9.41
$0.95 \leq m < 1.00$	4.29	4.68	5.02	11.94
$1.00 \leq m < 1.05$	4.52	4.74	5.00	11.40
$1.05 \leq m < 1.10$	4.16	4.31	4.59	7.29
	Panel B: Daily Open Interest			
$0.90 \leq m < 0.95$	793	4678	15116	3275
$0.95 \leq m < 1.00$	677	4603	14898	2623
$1.00 \leq m < 1.05$	1143	5705	18431	3504
$1.05 \leq m < 1.10$	1024	4813	18960	4177
	Panel C: Daily Volume			
$0.90 \leq m < 0.95$	48	207	1110	124
$0.95 \leq m < 1.00$	57	299	1228	182
$1.00 \leq m < 1.05$	106	385	1990	334
$1.05 \leq m < 1.10$	82	257	1806	218

This table shows the daily average number of options (Panel A), open interest (Panel B), and volume (Panel C) per bank for four different sub-samples and moneyness buckets. Statistics are calculated as averages per bank and median across all banks. Moneyness is defined as K/F. Note that $m > 1$ are out-of-the-money calls and $m < 1$ out-of-the-money puts.

high, with a sizable increase over the years. For the 2013-2019 sample, however, open interest seems to decreases again. This is attributable to available number of options per moneyness buckets, which approximately doubled. The finer strike grid explains the lower average open interest and volume per option in this sample. Overall, we find the data to be liquid.

3.2 Calibration and Implementation

LBC aims to measure the health of the financial sector. Although debt policies differ in reality, we make different pseudo-FIs comparable in default risk by specifying a target debt maturity τ^* and the relative expected loss ratio REL^*. Drechsler, Savov, and Schnabl (2021) find that the average repricing maturity of US commercial banks' liabilities is 0.43 years, which translates to approx. 150 days. We use this calibration as target debt maturity τ^*. We choose a value of $REL^* = 8\%$, resulting in an average leverage of 28 over our sample. Although we are not concerned about the actual leverage level but rather changes in leverage, Adrian and Shin (2010) show that the average investment bank has a leverage ratio of 25. Thus, our choice is a realistic assumption for banks and yields the most liquid time series so that we have an average of 15 banks per quarter. Nevertheless, we show in Section 4 that all subsequent results are robust to various changes in the calibration as long as the time series is reasonably liquid. Hence, REL^* and τ^* are only relevant

Table 2: LBC Summary Statistics

Panel A: LBC Summary Statistics						
Δ LBC		Mean	Std	Skew	Kurt	AC1
		0.00	0.27	-0.29	4.47	0.04
Panel B: Pairwise Correlations						
Δ LBC	RA	VRP	CAY	PD	AEM	HKM
	-0.52	0.02	-0.08	-0.12	-0.13	0.61

This table shows summary statistics for LBC changes (Panel A) and pairwise correlations (Panel B). RA denotes the risk aversion index of Bekaert, Engstrom, and Xu (2021), VRP the variance risk premium of Bollerslev, Tauchen, and Zhou (2009), CAY are consumption-wealth trend deviations from Lettau and Ludvigson (2001), and PD the price-dividend ratio calculated from all CRSP stocks. AEM and HKM are intermediary asset pricing factors from Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017), respectively.

to the magnitude of LBC, but not for its dynamics over time.

For each NY Fed Primary Dealer, we estimate an implied volatility surface on a grid ranging from the lowest to the highest values for maturity and moneyness. The grid is discretized with a one-day step size in the maturity dimension and a 0.01 step size in the moneyness dimension.[12] To estimate a smooth surface for each day, we require 1) a minimum of two different maturities and 2) at least two strikes per maturity. If one requirement is not satisfied, we eliminate the intermediary on that day so that aggregate measures do not rely on illiquid data. We use cubic spline interpolation for each maturity available to estimate the implied volatilities from the lowest to the highest strike. Then, we interpolate linearly between different maturities. Once we have a smooth volatility surface, we convert implied volatilities into call prices.[13]

Each call price reflects the market value of equity for an intermediary that holds its stock as total assets. The *book debt* of the intermediary is equal to the option's strike. To get *market values* of debt, one needs to adjust book debt by a term capturing the default risk of the intermediary. A put option effectively measures this. We, therefore, use put-call-parity to calculate put prices and are left with a fully observable balance sheet for all intermediaries. For each NY Fed Primary each day, we extract precisely the balance sheet that matches our calibration choice.

Table 2 details summary statistics for monthly LBC changes. The mean equals 0, and the standard deviation is 0.27. The slightly negative skewness of -0.29 and the kurtosis of 4.47 indicate some outliers on the left side of the distribution. The monthly autocorrelation is 0.04 and shows that changes in LBC are not serially dependent. Panel B of Table 2 presents pairwise correlations

[12] We define the minimum (0.6) and maximum (1.4) values for moneyness to reduce computational complexity.

[13] Note that our results are not driven by the construction of the volatility surfaces. Neither constructing the surface with a Gaussian kernel nor using the implied volatility surfaces provided by OptionMetrics changes our results.

to common proxies of expected risk premia. It is essential to clarify whether the asset pricing implications of LBC arise solely from being correlated to household risk aversion or whether the financial sector's health causes variations in risk premia. We note that the correlation to the risk aversion index (RA) of Bekaert, Engstrom, and Xu (2021) is -0.52. As LBC is tightly linked to the risk-bearing capacity of financial intermediaries, the negative correlation with economy-wide risk aversion is in line with intuition. We show, additionally, that our measure carries unique information. Other proxies such as the VRP, cay, or the price-dividend ratio calculated from the whole CRSP universe, exhibit no significant correlation to LBC. Correlation to the intermediary asset pricing factor of Adrian, Etula, and Muir (2014) is -0.13 and thus low. This was to be expected since they rely on a different intermediary universe and measure actual leverage while LBC comoves with the risk-bearing capacity of intermediaries. In times of high leverage, the soundness of the financial sector is low, and therefore both measures should be negatively correlated. The correlation to HKM is 0.61 as both measures use stock prices of the same intermediary universe as input. However, as we rely on a market-based valuation of debt, LBC carries distinct information.

3.3 Test Portfolios

To test whether our intermediary state variable matters for asset prices, we construct portfolios for seven different asset classes from 1996 to 2019 (if not otherwise specified). It is essential to have a cross-section of asset classes, given that frictions in some markets might be more pronounced than in others. Naturally, the more intermediated a market, the larger the effect of intermediaries in this market. The construction of our test portfolios again attempts to mimic our benchmark (HKM). The authors try to avoid arbitrariness in their choice and therefore rely on publicly available data if possible.

We start by collecting 25 Fama-French size- and value-sorted *equity* portfolios.[14] For *options*, we use the methodology of Constantinides, Jackwerth, and Savov (2013), who construct S&P 500 option portfolios with different moneyness and time-to-maturity. In particular, for both puts and calls, we target nine moneyness levels (0.9, 0.925, ..., 1.1) and three maturities (30, 60, 90 days) using a Gaussian weighting kernel. To apply linear regressions to the highly skewed returns and make their distribution close to normal, daily option portfolio returns are adjusted for leverage.

[14] As noted in Du, Hebert, and Wang (2020), the incorporation of large bank stocks in equity portfolio returns and the explanatory variable might cause problems in common asset pricing tests. The authors suggest reducing equity portfolios to six size and book-to-market portfolios. We test this specification as well but do not see any material change in our results.

The adjustment is carried out by investing ω^{-1} in the option and $1 - \omega^{-1}$ into the risk-free rate, where $\omega = \frac{\partial O}{\partial S} \times \frac{S}{O}$ denotes the option's delta times the ratio of stock to option price. As in HKM, we average the de-levered option portfolio returns across the three maturities and are left with 18 portfolios.

The *FX* class consists of 12 portfolios. For the first six, we update the time series of Lettau, Maggiori, and Weber (2014) and sort 52 currencies on their interest rate differential. The interest differential is calculated as $\frac{Future-Spot}{Spot}$. The second set of portfolios follows Menkhoff, Sarno, Schmeling, and Schrimpf (2012) and sorts 48 currencies into six portfolios based on their last month's performance (momentum). An overview of all countries we use for portfolio construction is given in Table A.2.

Commodity portfolios are constructed following Yang (2013) but differ due to different data sources. We obtain futures on 26 different commodities and drop the ones for which no complete time series is available, leaving us with 24 different commodities. Returns for each commodity class are calculated as the average across four different future maturities. We use continuous series from one month up to four months. Table A.3 shows all commodities considered.

The following asset classes differ from HKM due to data availability. For *corporate bonds*, we use seven BofA Merrill Lynch Total Bond Return indices that are sorted by credit rating.[15] Our six *sovereign bond* portfolios are constructed applying a two-way sort to the returns of 42 country indices. We first sort the sovereign bond returns by sensitivity to the U.S stock market into two portfolios and then by credit rating within each portfolio.[16]

Credit Default Swaps data are hard to obtain, especially on single-name CDS as in HKM. We, therefore, rely on the data provided by HKM. The authors construct 20 portfolios on individual name 5-year CDS contracts from 01/2001 until 12/2012.[17]

[15] The indices are publicly available via FRED: `https://fred.stlouisfed.org/categories/32413`.

[16] We note that the methodology is the same as in He, Kelly, and Manela (2017), but our country list differs in that we include not only emerging countries. A detailed list can be found in Table A.4.

[17] However, we do test our results using returns on 45 sector CDS indices sorted into 20 portfolios from 2012 until the end of our sample. Using sector indices as test assets improves our results slightly.

4 Asset Pricing

4.1 LBC in an Equilibrium Asset Pricing Model

To validate that LBC captures the marginal utility of financial intermediaries and guide our empirical asset pricing tests, we build on the intermediary model of He and Krishnamurthy (2013). The model's fundamental mechanism is that households can not directly invest in risky assets but can contract managers to form an intermediary that invests on their behalf. This implicitly abstracts from the traditional view that intermediaries are just a pass-through and makes the role of intermediaries in those markets marginal.

We solve and calibrate the model following He and Krishnamurthy (2013). To construct LBC, we define options on the levered return delivered by the intermediary, which is given by

$$\widetilde{dR_t} = r_t dt + \alpha_t^I (dR_t - r_t dt). \tag{8}$$

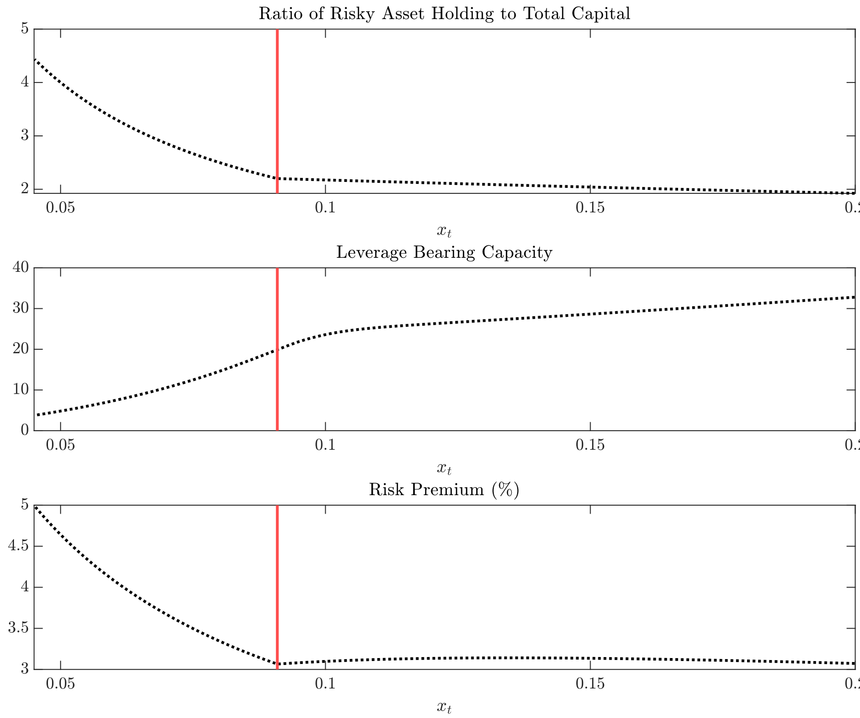
r_t denotes the risk-free rate, $dR_t = \frac{D_t \mathrm{d}t + \mathrm{d}P_t}{P_t}$ is the total return on the risky asset with price P_t, and α_t^I captures the leverage of the intermediary. The relevant state variable is the fraction of total wealth the intermediary owns, normalized by the price of the risky asset. We denote the state variable by $x_t = \frac{w_t}{w_t + H_t} P_t^{-1}$, where w_t is the intermediary wealth and H_t the wealth of the household. We assume that options are neither issued by the intermediary nor by the households and thus do not affect the equilibrium. In this setup, the price of a European call option is a function of x_t, the strike price K, and the time to maturity T:

$$C(x_t, K, T) = E_t^{\mathbb{Q}} \left[e^{-\int_t^{t+T} r_s \mathrm{d}s} \max\{ e^{\int_t^{t+T} \widetilde{dR_s} ds} - K, 0 \} \right]. \tag{9}$$

The price of a European put option is defined along the same lines for a payoff at maturity of $\max\{K - e^{\int_t^{t+T} \widetilde{dR_s} ds}, 0\}$. We calculate prices of call and put options for a wide range of strikes and maturity of six months via Monte Carlo simulations and construct pseudo intermediaries exactly as defined in the previous section.

Figure 7 shows the intermediary's leverage α_t^I (top panel), LBC (middle panel), and the risk premium (bottom panel) as functions of the intermediary's wealth share. As is evident, intermediary leverage and risk premiums decrease in the wealth share. The lower the wealth share, the higher the intermediary's leverage and risk premium in the economy. LBC, in contrast, increases

Figure 7: Model-based LBC and Leverage



This figure shows the model-implied leverage of the intermediary α_t^I, the Leverage Bearing Capacity, and the risk premium as a function of the intermediary's wealth share x_t. The red line depicts the barrier after which constraints become binding.

in x_t. When the wealth of the intermediary is low and marginal utility is high, the leverage bearing capacity decreases. Hence, changes in LBC govern the soundness of the intermediary sector. LBC is pro-cyclical and positively correlated with real-world financial intermediaries' wealth. We, therefore, expect a positive market price of risk in standard asset pricing tests.

4.2 Market Price of Risk

We now empirically examine whether LBC is indeed priced with a positive market price of risk in the cross-section of returns. Additionally, we ask whether LBC provides excess explanatory power over the well-established capital risk factor η. To test this, we closely follow the analysis of HKM to ensure the reliability of results concerning the empirical methodology.

We run time-series regressions of portfolio excess returns j in asset class k on the intermediary risk factor X and the market return R^M:

$$R_{t+1}^{j_k} - r_t^f = \alpha^{j_k} + \beta_X^{j_k} X_{t+1} + \beta_M^{j_k}(R_{t+1}^M - r_t^f) + \epsilon_{t+1}^{j_k}. \tag{10}$$

The exposures towards intermediary risk factors β_X and the market return β_M are assumed to be constant over time, since portfolio returns are not consistently available at higher frequencies and thus do not allow to estimate rolling-window betas. Portfolios in the individual asset classes are a balanced panel so that we have all returns available contemporaneously. In contrast, the overall portfolio consists of all individual portfolios and thus constitutes an unbalanced panel. In our main analysis, the risk factor X either includes only the change of LBC ψ or, additionally, a second risk factor (e.g., the capital risk factor η). To estimate the market price of risk across asset classes, we run cross-sectional regressions of average portfolio excess returns on the estimated betas in (10) within each asset class k

$$\hat{E}[R_{t+1}^{j_k} - r_t^f] = \gamma_k + \lambda_X^k \hat{\beta}_X^{j_k} + \lambda_M^k \hat{\beta}_M^{j_k} + \nu^{i_k}. \tag{11}$$

such that λ_X^k and λ_M^k are the asset-class specific market prices of risk, while γ_k is the cross-sectional intercept. We subsequently report annualized market prices of risk that are standardized across different portfolio loadings. Thus, a one standard deviation increase in time-series exposure towards LBC translates to an additional annual risk premium of λ_ψ^k percentage points (p.p.).

Panel A of Table 3 presents consistently positive market prices of risk for LBC across all asset classes from quarterly returns. The risk prices for one standard deviation in time-series exposure range from 0.14 p.p. for sovereign bond portfolios to 8.24 p.p. for commodities. Overall, investors require an additional annualized risk premium of 4.88 p.p. for a difference of one standard deviation in time-series betas between two portfolios. This is slightly higher than the 4.11 p.p. annual risk premium of the HKM capital risk factor from 1970 to 2012. In line with the predictions of intermediary asset pricing models, intermediary risk captured by LBC is thus positively priced in the cross-section of assets. The results are statistically highly significant for commodities, options, foreign exchange, credit default swaps, and the overall market price of risk. The estimate for corporate bond is significant at the 10% level. Haddad and Muir (2020) point out that asset classes might differ in their exposure to intermediary risk since intermediaries are more important in complex and costly markets. Indeed, the least intermediated asset classes — equity and sovereign bonds — are those where we do not find statistically significant results.

Panel B of Table 3 presents consistently positive market prices of risk for all intermediated asset

Table 3: Market Price of Risk

Panel A: Quarterly	Equity	Sov	Corp	Com	Opt	FX	CDS	All
LBC	0.69	0.14	1.10	8.24	5.51	1.70	1.99	4.88
	(0.73)	(0.26)	(1.64)	(2.39)	(3.69)	(3.41)	(4.33)	(2.07)
Market	−0.59	0.30	−0.23	−0.07	−0.36	1.39	0.03	3.00
	(−0.38)	(0.83)	(−0.21)	(−0.04)	(−0.61)	(2.08)	(0.06)	(1.01)
Constant	0.03	0.00	0.01	0.01	0.03	−0.01	0.00	0.00
	(1.72)	(0.97)	(2.36)	(0.94)	(1.75)	(−2.25)	(−2.04)	(0.06)
R^2	0.31	0.88	0.85	0.69	1.00	0.18	0.92	0.66
N	25	6	7	24	18	12	20	112
T	93	74	90	93	93	93	47	93

Panel B: Monthly	Equity	Sov	Corp	Com	Opt	FX	CDS	All
LBC	−0.35	−0.23	1.00	3.65	5.33	2.54	2.31	3.00
	(−0.41)	(−0.70)	(1.38)	(1.89)	(3.42)	(1.28)	(3.58)	(2.25)
Market	−0.90	0.51	−0.30	−0.72	−0.58	−1.78	−0.41	3.42
	(−0.80)	(1.01)	(−0.29)	(−0.39)	(−1.29)	(−1.55)	(−1.06)	(1.34)
Constant	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00
	(2.92)	(1.31)	(2.86)	(1.68)	(2.21)	(0.65)	(−3.25)	(0.04)
KZ-p	0.00	0.04	0.00	0.55	0.00	0.60	0.00	0.02
R^2	0.11	0.70	0.77	0.18	1.00	0.53	0.94	0.37
N	25	6	7	24	18	12	20	112
T	281	223	270	281	281	281	143	281

This table reports annualized market prices of risk (in p.p.) for one standard deviation difference in time-series exposure towards LBC and the market return. The estimates result from Fama-MacBeth regressions of quarterly (Panel A) and monthly (Panel B) portfolio returns from February 1996 to June 2019, where GMM-adjusted t-statistics are presented in parentheses. All panels include a cross-sectional intercept. KZ-p depicts the p-value of Kleibergen and Zhan (2020)'s F-test with the null hypothesis of misspecified risk premia. R^2 denotes the cross-sectional R-squared, N reports the number of cross-sectional portfolios within an asset class, and T is the number of observations.

classes estimated from monthly returns as well. These estimates range from 2.31 p.p. for credit default swaps to 5.33 p.p. for options, while the overall risk premium is 3 p.p.. As expected, the confidence intervals of LBC risk prices estimated from quarterly and monthly returns overlap for individual asset class estimates and the overall coefficient. Accordingly, LBC is significantly priced in the cross-section of commodities, options, credit default swaps, and the entire cross-section. HKM, however, rely on a data set that is twice as large but only report two significant market prices of risk at a monthly frequency. In contrast, their capital risk factor even yields negative estimates for commodities, a highly intermediated asset class. LBC thus does not only add statistical power at higher frequencies, but the signs of the market prices of risk are also in line with intermediary asset pricing models. Further, it yields economically and statistically reasonable results when bench-marking estimates from monthly returns with lower frequencies.

One major concern of empirical asset pricing tests is whether the exposure towards the risk factor is sufficiently dispersed between the test assets. Therefore, we rely on an F-statistic provided by Kleibergen and Zhan (2020) to test the possibility of misspecified risk premia on a monthly basis.

Indeed, we reject this hypothesis for equity, sovereign bonds, corporate bonds, options, CDS, and the full cross-section at the 5% level. For Commodities and FX, estimates and t-statistics must be interpreted cautiously since risk premia might be unidentified. Kroencke (2021), however, shows that the test is based on the assumption of normal i.i.d. returns and therefore rejects the null of misspecified risk premia too rarely. Nevertheless, Du, Hebert, and Wang (2020)'s CIP forward trading strategy does not correctly identify commodity risk premiums as well, but it does for FX. This suggests that LBC and the CIP forward trading strategy complement each other in explaining returns.

4.3 Horse Race

As LBC successfully explains returns in the cross-section of test assets, we now run a horse race against the intermediary asset pricing factor proposed by HKM. Therefore, we include the change in the Leverage Bearing Capacity ψ as well as the capital risk factor η in our regression models. The first row of Table 4 reports the results for Leverage Bearing Capacity. Indeed, the prices of leverage bearing risk are constantly positive and remain significant at least at the 5% level for commodities, options, CDS, and the pooled portfolio. Most importantly, even after including the measure of HKM, the coefficient for LBC remains almost unchanged. Since both measures are correlated, it is natural to expect that the significance levels diminish slightly. In contrast to the Leverage Bearing Capacity, the third row of Table 4 shows that the prices of risk for the capital ratio of HKM at a quarterly frequency are not consistently positive once we add LBC. Only the coefficient for foreign exchange is significant at the 10% level. The annualized risk premia for the unbalanced portfolio of 0.16 p.p. is economically as well as statistically meaningless. Hence, we conclude that even at a quarterly frequency, at which HKM construct their existing measure, LBC contains excess explanatory power for the pricing of assets.

Table 4: Horserace HKM

	Equity	Sov	Corp	Com	Opt	FX	CDS	All
LBC	0.69	−0.01	0.90	6.51	5.31	1.01	1.65	4.63
	(0.78)	(−0.01)	(1.41)	(2.06)	(3.75)	(0.69)	(4.09)	(2.72)
HKM	−0.61	0.73	0.09	−2.81	0.13	3.47	0.47	0.16
	(−0.42)	(0.69)	(0.15)	(−0.85)	(0.57)	(1.85)	(1.14)	(0.07)
Market	−1.12	0.75	−0.12	0.16	−0.28	0.95	−0.03	3.45
	(−0.54)	(0.78)	(−0.15)	(0.07)	(−0.49)	(0.44)	(−0.10)	(1.27)
Constant	0.03	0.00	0.01	0.01	0.03	0.00	0.00	0.00
	(2.02)	(0.91)	(1.78)	(0.69)	(1.51)	(−0.08)	(−2.00)	(0.02)
R^2	0.35	0.99	0.85	0.81	1.00	0.67	0.92	0.74
N	25	6	7	24	18	12	20	112
T	93	74	90	93	93	93	47	93

This table reports annualized market prices of risk (in p.p.) for one standard deviation difference in time-series exposure towards LBC, the capital risk factor of HKM, and the market return. The estimates result from Fama-MacBeth regressions of quarterly portfolio returns from Q2/1996 to Q2/2019, where GMM-adjusted t-statistics are presented in parentheses. We include a cross-sectional intercept in the regression. R^2 denotes the cross-sectional R-squared, N reports the number of cross-sectional portfolios within an asset class, and T is the number of observations.

4.4 Impact of Uncertainty

We now examine how uncertainty contributes to the pricing performance of LBC and existing measures of intermediaries' health. As shown in the simulation and event studies in Section 2, uncertainty directly affects LBC, while the effect on measures solely based on equity values is less straightforward. We subsequently test whether the pricing performance is subsumed by uncertainty, and thus the measures incorporate additional information for the cross-section of asset returns. We proxy uncertainty using parametric and nonparametric measures of financial sectors' stock return volatility. Specifically, we use value-weighted stock returns of all primary dealers and apply the GARCH(1,1) model of Glosten, Jagannathan, and Runkle (1993)

$$\sigma_{t,GJR} = \sqrt{\kappa + \gamma\sigma_{t-1} + \alpha\epsilon_{t-1}^2 + \mathbb{1}_{\epsilon<0}\xi\epsilon_{t-1}^2}\,. \tag{12}$$

Further, we calculate monthly realized volatilities estimated from scaled daily squared returns

$$\sigma_{t,RV} = \sqrt{\frac{21}{N}\sum_{i=0}^{N-1} r_{t-i}^2}\,. \tag{13}$$

We include changes of both measures separately in the previous Fama-MacBeth regressions and report results for monthly horizons in Table 5. Across all model specifications, we find that both risk prices of conditional and unconditional uncertainty have the expected negative sign. In states of increasing uncertainty, the marginal utility of investors is high, and therefore investors pay

Table 5: Market Price of Risk and Uncertainty

	I	II	III	IV	V	VI
HKM	0.00		−0.37	−1.32		−1.10
	(−0.08)		(−0.25)	(−0.42)		(−0.57)
σ_{GJR}	−0.80	−2.52	−1.78			
	(−2.73)	(−1.37)	(−1.61)			
σ_{RV}				−1.70	−1.88	−1.57
				(−0.81)	(−1.09)	(−1.20)
LBC		2.17	2.74		2.63	3.24
		(1.83)	(1.81)		(1.73)	(1.75)
KZ-p	0.03	0.02	0.06	0.03	0.23	0.24
R^2	0.54	0.50	0.65	0.39	0.37	0.56
N	112	112	112	112	112	112
T	280	280	280	281	281	281

This table reports annualized market prices of risk (in p.p.) for one standard deviation difference in time-series exposure towards changes in LBC, the capital risk factor of HKM, conditional uncertainty from a GJR-GARCH model, and realized uncertainty. The estimates result from Fama-MacBeth regressions of monthly portfolio returns from February 1996 to June 2019, where GMM-adjusted t-statistics are presented in parentheses. All regressions include a cross-sectional intercept, a constant, and the market return. KZ-p depicts the p-value of Kleibergen and Zhan (2020)'s F-test with the null hypothesis of misspecified risk premia. R^2 denotes the cross-sectional R-squared, N reports the number of cross-sectional portfolios within an asset class, and T is the number of observations.

additional premia to hedge their exposure towards uncertainty. In the first model, HKM loses all its economic and statistical explanatory power for the cross-section of asset returns when we include the estimate of conditional uncertainty. This finding is less pronounced but still evident when using realized variance in column four instead. In contrast, LBC remains significant at the 10% level for both uncertainty measures in columns two and five, while the uncertainty estimates become statistically insignificant. For a one standard deviation difference in exposure towards LBC, the risk premium is 2.17 p.p. even if we control for changes in conditional uncertainty. This estimate is slightly lower than 3 p.p. in Table 3, suggesting that 72.3% of the risk premium is not attributable to conditional uncertainty. This finding is robust even if we include all variables in one linear regression model in the third and sixth columns.[18]

The results of our analysis are thus twofold. First, we find that the explanatory power of HKM at the monthly level is almost entirely subsumed by the uncertainty of underlying stock returns. Once we include estimates for uncertainty, the economic and statistical explanatory power disappears. Second, we show that LBC also covers this dimension but has additional explanatory power beyond it. This could be, for example, asymmetric risks that are not (accordingly) represented in realized or conditional volatilities. A factor model with LBC and market returns provides excess explanatory power over existing measures, even if we include proxies for uncertainty.

[18]Including all variables in one regression model raises potential concerns regarding multicollinearity and correctly identified risk premia according to the Kleibergen and Zhan (2020) F-test. We, therefore, only provide the results as additional robustness tests.

4.5 Common Risk Factors

Leverage Bearing Capacity, our measure to capture intermediaries' marginal utility, has strong explanatory power as a pricing factor for many asset classes. In this section, we test whether LBC constitutes a risk factor or if other common risk factors subsume its pricing power. We regress the returns of all available portfolios on LBC and other factors that explain the cross-section of returns. The models or factors we set LBC relative to include the CAPM, Fama-French three-factor (FF3F) and five-factor model (FF5F), momentum (C4F), as well as the liquidity factor (PS) of Pástor and Stambaugh (2003). Table 6 presents the estimates at monthly frequency.

Table 6: Comparison to Other Risk Factors

	CAPM	FF3F	C4F	FF5F	PS
LBC	3.00	3.36	3.30	2.99	3.06
	(2.25)	(2.09)	(1.88)	(1.98)	(2.09)
Market	3.42	3.82	4.03	3.50	3.47
	(1.34)	(1.61)	(1.75)	(1.52)	(1.41)
SMB		0.17	0.02	1.39	
		(0.11)	(0.01)	(1.26)	
HML		−1.40	−1.54	−0.99	
		(−0.68)	(−0.70)	(−1.06)	
MOM			0.32		
			(0.20)		
RMW				2.28	
				(1.72)	
CMA				−0.28	
				(−0.29)	
PS					−0.34
					(−0.12)
Constant	0.00	0.00	0.00	0.00	0.00
	(0.04)	(−0.02)	(0.01)	(−0.37)	(−0.08)
KZ-p	0.02	0.01	0.16	0.13	0.25
KZ-p w/o LBC	0.00	0.00	0.17	0.13	0.22
R^2	0.37	0.45	0.45	0.62	0.38
R^2 w/o LBC	0.21	0.25	0.26	0.48	0.21
N	112	112	112	112	112
T	281	281	281	281	281

This table reports annualized market prices of risk (in p.p.) for one standard deviation difference in time-series exposure towards LBC and other common risk factors. CAPM includes the market factor as control, FF3F adds size and book-to-market, C4F adds momentum, and FF5F all five factors from Fama and French (2015). The estimates result from Fama-MacBeth regressions of monthly portfolio returns from 02/1996 to 06/2019, where GMM-adjusted t-statistics are presented in parentheses. We include a cross-sectional intercept in the regression. KZ-p depicts the p-value of Kleibergen and Zhan (2020)'s F-test with the null hypothesis of misspecified risk premia for regressions including and excluding LBC. R^2 denotes the cross-sectional R-squared, N reports the total number of portfolios and T is the number of observations.

Across all model specifications, the price of leverage bearing risk remains significant. T-statistics range from 1.88 in the momentum model to 2.25 in the CAPM. The magnitude of the (standardized) coefficients remains stable throughout all specifications. We find the most extensive loading in the Fama-French three-factor model (3.36) and the lowest in the five-factor model (2.99). Thus, a one standard deviation difference in loadings translates to an extra annualized risk premia of 2.99 p.p. in the FF5F and 3.36 p.p. in the FF3F. The stability of coefficients and the fact that no other risk factor drives out the significance of LBC is unexpected, given that all other models are statistically motivated and lack theoretical validation.[19]

Comparing the cross-sectional explanatory power across models with and without LBC as an explanatory variable, we find that the average R^2 increases by 68%. The effect is highest for the PS model, with an increase of 81%, and lowest for the Fama-French five-factor model, with an increase of 29%. Without LBC in the model, changes in R^2 are by far less significant. For instance, the R^2 of 21% in the CAPM increases to 25% when Fama-French's two additional factors are added. In contrast, the explanatory power in the CAPM increases to 37% when we include LBC in the model. The well model fit is unlikely driven by a strong factor structure in the portfolios, as test assets consist of more than 100 portfolios across seven different asset classes (Lewellen, Nagel, and Shanken, 2010). Further, we reject the hypothesis of misspecified risk premia for LBC in the CAPM and FF3F model at the 5% level. The risk premiums in the other models are potentially inaccurate, but this is also the case if we omit LBC. While the risk premiums of LBC and FF3F risk factors appear to be correctly specified, the other risk factors distort the results and explain the slightly declining t-statistics for our measure.

4.6 Robustness

In this section, we test the robustness of our results concerning calibration, alternative test portfolios, sub-samples, naïve weighting of intermediaries, and other financial as well as non-financial risk factors. Corresponding Figures and Tables are provided in B.

Calibration. Naturally, one question to ask is whether our results rely only on the calibration choices of the target debt maturity and the discounted expected loss ratio. Therefore, we estimate market prices of risk for LBCs extracted from all liquid combinations of REL^* and τ^*. We only report estimates when the sample comprises at least one observation in each period and more than ten pseudo-FIs on average. Figure B.1 presents the GMM-adjusted t-statistics for the overall market price of risk at a quarterly frequency. 114 (171) of 171 liquid combinations are significant at the 5% (10%) level, implying that our results are robust to various changes in calibration. This also holds for monthly frequency, where 95 (131) of 158 estimates are significant at the respective levels.

[19] Although most of the factors included are known to explain equities and have not been tested across asset classes.

The few results where we cannot reject the null hypothesis are almost borderline significant and only slightly above the liquidity requirement. Overall, our results rely on economically motivated calibrations but are robust to changes in debt maturity and expected loss ratio as long as the time-series of LBC is reasonably liquid.

Alternative Test Portfolios. Even though we follow HKM in constructing the test portfolios as close as possible, we deviate from their approach for corporate and sovereign bonds as well as CDS due to data availability. To test whether our choice of test portfolios drives our results, we estimate the market prices of risk for their original portfolios. The sample period is quite short and ranges from 1996 to 2012, but the first row of Table B.1 depicts that our results improve. Corporate bonds, commodities, options, FX, and credit default swaps are highly significant at the 5% level. The overall market price of risk is significant at the 1% level and lies in the same confidence interval as previous estimates (3.78 p.p. to 4.89 p.p.). Panel B presents risk prices when benchmarking LBC and the capital risk factor. All results improve for LBC compared to the main analysis since LBC is still significantly priced in 4 out of 7 asset classes and for the full cross-section. The capital risk factor, however, loses its explanatory power across all asset classes. The market price of risk for LBC is therefore robust to alternative test portfolios.

Excluding the Great Recession. Since our sample period comprises the Great Recession in 2008, we examine whether our results are driven by a few data points with extreme negative returns associated with low LBC. Therefore, we present results in Table B.2 when excluding all observations from December 2007 to June 2009. GMM-adjusted t-statistics of overall market prices of risk for LBC improve at quarterly (2.07 to 2.25) and monthly frequency (2.25 to 2.61). This pattern speaks in favor of an even more reliable time series of LBC when we exclude the financial crisis. This is probably due to LBC relying on fewer pseudo-FIs when macroeconomic conditions tighten.[20] Panel C reports the market price of risk for the test portfolios of HKM. The explanatory power for corporate bonds and commodities diminishes, representing the trade-off between the less liquid financial crisis and short sample periods. The overall economic and statistical significance of LBC, however, is robust to excluding the Great Recession.

Equally-weighted LBC. The heterogeneity across Primary Dealers raises the question of whether the value-weighted LBC derives its explanatory power exclusively from few but large intermediaries. This argument, however, does not contradict the theory since most large intermediaries have access to complex markets and should be marginal in pricing assets. Nevertheless, we still expect

[20]Technically, the period is characterized by fewer ITM call options available. These options are necessary for the construction of pseudo-FIs.

explanatory power for medium-sized NY Fed Primary Dealers as well. Therefore, we present market prices of risk for an equally-weighted LBC in Table B.3 at quarterly and monthly frequency. While point estimates almost unchanged, the explanatory power of the market prices of risk diminishes slightly for quarterly returns but remains significant at least at the 10% level. Hence, more weight to larger intermediaries improves the reliability of LBC. Investors require risk premia for being exposed to aggregate intermediary risk where larger intermediaries naturally have a higher share.

Intermediary Risk Factors. While we extensively tested LBC against the HKM capital risk factor, we now examine its excess explanatory power LBC compared to other intermediary risk factors at a quarterly frequency. Panel A of Table B.4 presents results compared to the broker-dealer book leverage of Adrian, Etula, and Muir (2014). Indeed, exposure towards AEM earns negative but insignificant risk premia, while the market price of risk for LBC rises slightly and keeps its significance. However, risk prices for CDS are significant for AEM, while LBC loses some of its explanatory power. Since AEM relies on broker-dealers' book values, this finding sparks the discussion of choosing the correct underlying in empirical intermediary asset pricing.[21] Further, we benchmark LBC of Primary Dealers with their value-weighted equity return in Panel B. While both measures are highly correlated, we find that only LBC carries significant explanatory power in explaining the cross-section of returns.

Non-Intermediary Risk Factors. The explanatory power of Primary Dealers' LBC is a necessary but not a sufficient condition for intermediary asset pricing. While intermediaries must be marginal, households are not allowed to be contemporaneous. Therefore, we examine the market price of risk for LBC while controlling for cay of Lettau and Ludvigson (2001) in Panel A and risk aversion of Bekaert, Engstrom, and Xu (2021) in Panel B of Table B.5. Each of them proxies the overall household or market risk-bearing capacity. First, none of those measures takes away the statistical and economic significance of the overall market price of risk. We even find that market prices for cay are effectively zero. The point estimates for risk aversion depict the expected negative sign for options, FX, and CDS but do not add any additional explanatory power in terms of statistical significance. LBC of Primary Dealers is priced in the cross-section of returns and thus carries unique information that is not captured by common proxies of household risk aversion.

[21]See He, Kelly, and Manela (2017) for an in-depth discussion.

5 Conclusion

The leverage of financial intermediaries is of crucial importance for intermediary asset pricing. Existing empirical leverage ratios rely on book values of debt because corporate bonds are illiquid, noisy, and not all assets of bond-issuing companies have observable market values. However, book values of debt are naturally backward-looking, slow-moving, of low frequency, and do not capture higher-moment risks such as uncertainty or downside risks. This raises concerns about the accuracy of empirical measures of intermediaries' health.

We use option prices to circumvent the disadvantages of book values and compute the Leverage Bearing Capacity (LBC) of financial intermediaries. We establish that LBC reflects the health of financial intermediaries in simulation and case studies, a general equilibrium model, and empirical asset pricing tests. LBC is available at any frequency, which makes it a useful tool for further tests in intermediary asset pricing.

Our theoretical and empirical results indicate that uncertainty is crucial to understand intermediary constraints. Extending intermediary models by time-varying macroeconomic uncertainty or time-varying constraints might be a fruitful avenue for future research.

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Appendix

A Data

In this section, we provide details about the origin of the data used in our main analysis and robustness tests.

Underlying

NY Fed Primary Dealer: A list of all financial intermediaries used in the main analysis can be found in Table A.1. The raw data come from
`https://www.newyorkfed.org/markets/primarydealers`.

Portfolios

Equity: We use 25 portfolios provided by Kenneth French. Data are available at
`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

Sovereign Bonds: Table A.4 gives an overview of all indices and their Reuters tickers used in the construction of our six portfolios.

Corporate Bonds: We use seven indices, categorized by credit rating, that can be found here
`https://fred.stlouisfed.org/categories/32413`.

Commodities: A list of all commodities and their ticker is given in Table A.3. The data are downloaded via Thomson Reuters Datastream.

Options: We use OptionMetrics daily data for S&P 500 options and apply the same filters as in Constantinides, Jackwerth, and Savov (2013).

Foreign Exchange: Table A.2 provides an overview of all countries we use to form Momentum and Interest Rate Differential portfolios. The data are downloaded via Thomson Reuters.

CDS: We rely on the 20 CDS portfolios of He, Kelly, and Manela (2017). The data can be found at `http://apps.olin.wustl.edu/faculty/manela/data.html`.

Intermediary Risk Factors

AEM: The broker-dealer leverage ratio from Adrian, Etula, and Muir (2014) is available at
`https://sites.google.com/site/tylersmuir/home/data-and-code`.

HKM: The Primary Dealer capital risk factor can be downloaded at
`https://voices.uchicago.edu/zhiguohe/data-and-empirical-patterns/intermediary-capital-ratio-and-risk-factor/`.

Other Risk Factors

cay: Data for cay be found at `https://sites.google.com/view/martinlettau/data`.

RA: Data for the risk aversion index of Bekaert, Engstrom, and Xu (2021) be found at `https://www.nancyxu.net/risk-aversion-index`.

VRP: Variance risk premium data is available at monthly frequency via `https://sites.google.com/site/haozhouspersonalhomepage/`.

PD: The price-dividend ratio is determined with the full CRSP universe, using total returns and returns without dividends.

Table A.1: NY Fed Primary Dealer

Name	Option ID	CUSIP	Primary Dealer		Sample	
			Start Date	End Date	Start Date	End Date
ABN AMRO HLDG NV	100880	00093710	1998-09-29	2006-09-15	1998-09-29	2006-09-15
BANKAMERICA CORP-OLD	5086	06605010	-	1998-09-30	1996-01-04	1998-09-30
BANK AMER CORP	101966	06605F10	-	-	1996-01-04	2019-06-28
BARCLAYS PLC	102016	06738E20	-	-	2007-11-08	2019-06-28
BANK MONTREAL QUE	101977	06367110	2000-02-15	-	2002-01-10	2019-06-28
BANK N S HALIFAX	115462	06414910	2011-10-04	-	2011-10-04	2019-06-28
BEAR STEARNS COS INC	102061	07390210	-	2008-10-01	1996-01-04	2008-05-30
BANKERS TRUST CORP	5087	06636510	-	1999-06-04	1996-01-04	1999-06-03
CITICORP	5197	17303410	-	1998-10-07	1996-01-04	1998-10-07
CITIGROUP INC	103049	17296710	-	-	1996-01-04	2019-06-28
COUNTRYWIDE FINANCIAL CORP	103477	22237210	2004-01-15	2008-07-15	2004-01-15	2008-06-30
JPMORGAN CHASE & CO	102936	16372210	-	-	1996-01-04	2019-06-28
CREDIT SUISSE GROUP AG	123324	22540110	-	-	2005-02-14	2019-06-28
DEUTSCHE BANK AG	113058	D1819089	-	-	2001-10-04	2019-06-28
DEAN WITTER DISCOVER & CO	7737	24240V10	-	1998-04-30	1996-01-04	1997-05-29
FIRST CHICAGO NBD CORP	5644	31945A10	-	1999-03-31	1996-01-04	1998-10-01
GOLDMAN SACHS GROUP INC	105329	38141G10	-	-	1999-08-11	2019-06-28
HSBC HLDGS PLC	105495	40428040	-	-	1999-12-30	2019-06-28
JEFFERIES GROUP INC NEW	106551	47231910	2009-06-18	2013-02-28	2009-06-18	2013-02-28
JEFFERIES FINANCIAL GROUP IN	106905	52728810	2013-03-01	-	2013-03-01	2019-06-28
J.P. MORGAN & CO. INC.	107693	61688010	-	2000-12-31	1996-01-04	2000-12-29
LEHMAN BROS HLDGS INC	106893	52490810	-	2008-09-22	1996-01-04	2008-09-17
MERRILL LYNCH & CO INC	107455	59018810	-	2009-02-11	1996-01-04	2008-12-31
MF GLOBAL HLDGS LTD	133879	55277J10	2011-02-02	2011-10-31	2011-02-02	2011-10-28
MIZUHO FINL GROUP INC	128129	60687Y10	2002-04-01	-	2008-10-28	2019-06-28
MORGAN STANLEY	107704	61744610	-	-	1996-01-04	2019-06-28
NOMURA HLDGS INC	113445	65535H20	-	-	2006-09-11	2019-06-28*
BANK ONE CORP	101988	06423A10	1999-04-01	2004-08-01	1999-04-01	2004-06-30
PAINE WEBBER GROUP	5695	69562910	-	2000-12-04	1996-01-04	2000-10-20
ROYAL BK SCOTLAND GROUP PLC	134585	78009772	-	-	2009-02-03	2019-06-28
ROYAL BK CDA MONTREAL QUE	109722	78008710	2009-07-08	-	2009-07-08	2019-06-28
TORONTO DOMINION BK ONT	111089	89116050	2014-02-11	-	2014-02-11	2019-06-28
UBS AG	112341	H8920G15	-	2015-01-07	2000-05-16	2015-01-07
UBS GROUP AG	205788	H4209710	2015-01-08	-	2015-01-08	2019-06-28
WELLS FARGO CO NEW	111953	94974610	2016-04-18	-	2016-04-18	2019-06-28
ZIONS BANCORPORATION N.A	112233	98970110	-	2002-03-31	1997-06-03	2002-03-28

*Nomura was temporarily withdrawn from the list of primary dealers from November 30, 2007, to July 26, 2009.

This table presents all NY Fed Primary Dealers from 1996 to 2019 that we use in our analysis. We only report the entity if we successfully hand-matched CRSP stock data with OptionMetrics option data after applying standard filters. The table depicts the OptionMetrics entity name, security ID and CUSIP. Further, we show the time period when the entity was Primary Dealer as well when we actually include it in our sample. These periods might differ due to data availability. If the start or end date is denoted by '-', the entity was Primary Dealer already before our sample starts and/or beyond the sample ends.

Table A.2: Foreign Exchange Portfolios

Country	Currency Code	Momentum	Interest Rate Differential	Start Date	End Date
United Arab Emirates	AED		X	01/1997	06/2019
Argentina	ARS		X	03/2004	06/2019
Austria	ATS		X	01/1997	12/1998
Australia	AUD	X	X	01/1996	06/2019
Belgium	BEF	X	X	01/1997	12/1998
Bulgaria	BGN	X		03/2004	06/2019
Brazil	BRL	X	X	03/2004	06/2019
Canada	CAD	X	X	01/1996	06/2019
Switzerland	CHF	X	X	01/1996	06/2019
Chile	CLP		X	03/2004	06/2019
China	CNY		X	10/2009	06/2019
Colombia	COP		X	03/2004	06/2019
Cyprus	CYP	X		03/2004	12/2007
Czechia	CZK	X	X	01/1997	06/2019
Germany	DEM	X	X	01/1996	12/1998
Denmark	DKK	X	X	01/1996	06/2019
Egypt	EGP	X	X	03/2004	06/2019
Spain	ESP	X	X	01/1997	12/1998
European Union	EUR	X	X	01/1999	06/2019
Finland	FIM	X	X	01/1997	12/1998
France	FRF	X	X	01/1996	12/1998
United Kingdom	GBP	X	X	01/1996	06/2019
Greece	GRD	X	X	01/1997	12/2000
Honk Kong	HKD	X	X	01/1996	06/2019
Croatia	HRK	X		03/2004	06/2019
Hungary	HUF	X	X	10/1997	06/2019
Indonesia	IDR	X	X	01/1997	06/2019
Ireland	IEP	X	X	01/1996	12/1998
Israel	ILS	X	X	03/2004	06/2019
India	INR	X	X	10/1997	06/2019
Iceland	ISK	X		03/2004	06/2019
Italy	ITL	X	X	01/1996	12/1998
Jordan	JOD		X	03/2004	06/2019
Japan	JPY	X	X	01/1996	06/2019
South Korea	KRW	X	X	02/2002	06/2019
Kuwait	KWD	X	X	01/1997	06/2019
Sri Lanka	LKR		X	07/2011	06/2019
Morocco	MAD		X	03/2004	06/2019
Mexico	MXN	X	X	01/1997	06/2019
Malaysia	MYR	X	X	01/1996	06/2019
Netherlands	NLG	X	X	01/1996	12/1998
Norway	NOK	X	X	01/1996	06/2019
New Zealand	NZD	X	X	01/1996	06/2019
Peru	PEN		X	03/2004	06/2019
Philippines	PHP	X	X	01/1997	06/2019
Pakistan	PKR		X	03/2004	06/2019
Poland	PLN	X	X	02/2002	06/2019
Portugal	PTE	X	X	01/1997	12/1998
Russia	RUB	X	X	03/2004	06/2019
Saudi Arabia	SAR	X	X	01/1997	06/2019
Sweden	SEK	X	X	01/1996	06/2019
Singapore	SGD	X	X	01/1996	06/2019
Slovenia	SIT	X		03/2004	12/2006
Slovakia	SKK	X		02/2002	12/2008
Thailand	THB	X	X	01/1997	06/2019
Turkey	TRY		X	01/1997	06/2019
Taiwan	TWD	X	X	01/1997	06/2019
Ukraine	UAH	X		03/2004	06/2019
South Africa	ZAR	X	X	01/1996	06/2019

This table provides an overview of all currencies used to construct FX momentum and interest rate differential portfolios.

Table A.3: Commodity Portfolios

Name	Reuters Ticker	Exchange	Currency	c1	c2	c3	c4
Aluminium	LAHC	London Metal Exchange	USD	X	X	X	X
Canola	WRSC	ICE Futures Canada	CAD	X	X		
Cocoa	NCCC	ICE Futures U.S.	USD	X	X		
Coffee	NKCC	ICE Futures U.S.	USD	X	X		
Copper	NHGC	New York Mercantile Exchange (COMEX Division)	USD	X	X	X	X
Corn	CCFC	eCBOT	USD	X	X		
Cotton	NCTC	ICE Futures U.S.	USD	X	X		
Crude Oil	NCLC	New York Mercantile Exchange (NYMEX)	USD	X	X	X	X
Feeder Cattle	CFDC	Chicago Mercantile Exchange	USD	X	X	X	
Gold	NGCC	New York Mercantile Exchange (COMEX Division)	USD	X	X	X	X
Heating Oil	NHOC	New York Mercantile Exchange (NYMEX)	USD	X	X	X	X
Lean Hogs	CLGC	Chicago Mercantile Exchange	USD	X	X	X	
Live Cattle	CLDC	Chicago Mercantile Exchange	USD	X	X	X	
Lumber	CLBC	Chicago Mercantile Exchange	USD	X	X		
Natural Gas	NNGC	New York Mercantile Exchange (NYMEX)	USD	X	X	X	X
Oats	COFC	CBOT - Floor	USD	X	X		
Palladium	NPAC	New York Mercantile Exchange (NYMEX)	USD	X	X	X	X
Platinum	NPLC	New York Mercantile Exchange (NYMEX)	USD	X	X	X	
Silver	NSLC	New York Mercantile Exchange (COMEX Division)	USD	X	X	X	
Soybean Meal	CSMC	eCBOT	USD	X	X		
Soybean Oil	CSNC	eCBOT	USD	X	X		
Soybeans	CSYC	eCBOT	USD	X	X		
Sugar	NSBC	ICE Futures U.S.	USD	X	X		
Wheat	KKKC	Kansas City Board of Trade	USD	X	X		

This table provides an overview of all commodities used. c1 refers to the Datastream Continuous Series of future prices of the nearest contract rolled over at the last trading day, c2 to the second nearest, and so forth.

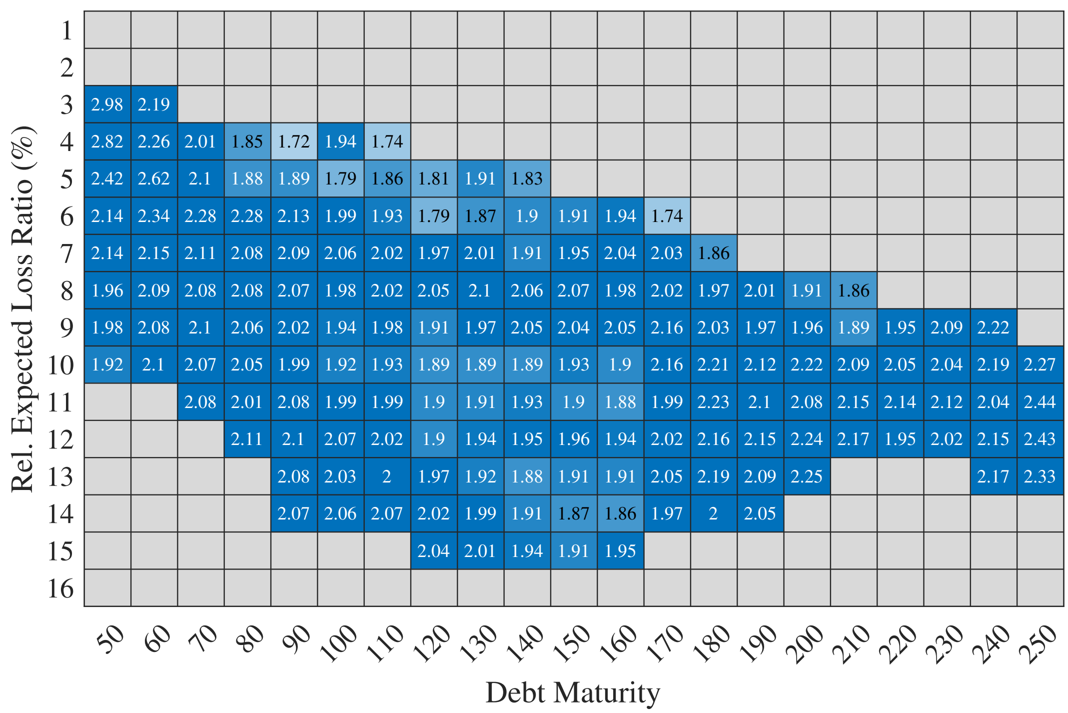
Table A.4: Sovereign Bond Portfolios

Country	**Name**	**Reuters Ticker**
Chile	S&P CHILE SOV BOND PRICE INDEX	SPFICHL
Colombia	S&P COLOMBIA SOV BOND PRICE INDEX	SPBVCSB
Mexico	S&P MEXICO SOV BOND PRICE INDEX	SPFIMEX
Peru	S&P PERU SOV BOND PRICE INDEX	SPFIPER
China	S&P CHINA SOVEREIGN BOND PRICE INDEX	SPCHSVI
India	S&P INDONESIA SVREIN BOND PRICE INDEX	SPIDSVI
Korea (the Republic of)	S&P SOUTH KOREA SOV BOND PRICE INDEX	SPBKRSV
Malaysia	S&P MALAYSIA SOVREIN BOND PRICE INDEX	SPMYSVI
Philippines	S&P PHILIPPINES SOVE BOND PRICE INDEX	SPPHSVI
Thailand	S&P THAILAND SOVREIN BOND PRICE INDEX	SPTHSVI
South Africa	S&P SA SOV BOND PRICE INDEX	SPSFIZA
Tunisia	S&P TUNISIA SOV BOND PRICE INDEX	SPSFITN
Morocco	S&P MOROCCO SOV BOND PRICE INDEX	SPSFIMA
Ghana	S&P GHANA SOV BOND PRICE INDEX	SPSFIGH
India	S&P BSE INDIA SVREIN BOND PRICE INDEX	SPBISVI
Japan	S&P JAPAN SOV BOND PRICE INDEX	SPBJPSV
Singapore	S&P SINGAPORE SOV BOND PRICE INDEX	SPBSGSV
Taiwan	S&P TAIWAN SOVEREIGN BOND PRICE INDEX	SPTWSVI
Norway	S&P NORWAY SOV BOND PRICE INDEX	SPSFINO
Denmark	S&P DENMARK SOV BOND PRICE INDEX	SPFIDKS
Austria	S&P AUSTRIA SOV BOND PRICE INDEX	SPBDEAT
Belgium	S&P BELGIUM SOV BOND PRICE INDEX	SPBDEBE
Finland	S&P FINLAND SOV BOND PRICE INDEX	SPBDEFI
France	S&P FRANCE SOV BOND PRICE INDEX	SPBDEFR
Germany	S&P GERMANY SOV BOND PRICE INDEX	SPBDEDE
Greece	S&P GREECE SOV BOND PRICE INDEX	SPBDEGR
Ireland	S&P IRELAND SOV BOND PRICE INDEX	SPBDEIE
Italy	S&P ITALY SOV BOND PRICE INDEX	SPBDEIT
Luxembourg	S&P LUXE SOV BOND PRICE INDEX	SPBDELU
Netherlands	S&P NETH SOV BOND PRICE INDEX	SPBDENL
Portugal	S&P PORTUGAL SOV BOND PRICE INDEX	SPBDEPT
Spain	S&P SPAIN SOV BOND PRICE INDEX	SPBDEES
Switzerland	S&P SWISS SOV BOND PRICE INDEX	SPSFISW
Israel	S&P ISRAEL SOV BOND PRICE INDEX	SPSFIIL
Botswana	S&P BOTSWANA SOV BOND PRICE INDEX	SPSFIBW
Kenya	S&P KENYA SOV BOND PRICE INDEX	SPSFIKE
Namibia	S&P NAMIBIA SOV BOND PRICE INDEX	SPSFINA
Tanzania	S&P TANZANIA SOV BOND PRICE INDEX	SPSFITZ
Uganda	S&P UGANDA SOV BOND PRICE INDEX	SPSFIUG
Zambia	S&P ZAMBIA SOV BOND PRICE INDEX	SPSFIZM
Australia	S&P AUSTRALIA SOV BOND PRICE INDEX	SPBAUST
New Zealand	S&P NZ SOV BOND PRICE INDEX	SPBNZSV

This table provides an overview of all country indices used to construct our sovereign portfolios.

B Robustness

Figure B.1: Significance of Overall Market Price of Risk for Different Calibrations



This figure presents GMM-adjusted t-statistics for the overall quarterly LBC market price of risk for different calibrations. The coefficients are from Fama-MacBeth regressions of quarterly portfolio returns covering seven different asset classes and 112 portfolios in total. We only report estimates when the sample comprises at least one observation in each quarter and more than 10 pseudo-FIs on average.

Table B.1: Market Price of Risk with Portfolios of HKM

Panel A: Quarterly with HKM Portfolios

	Equity	Sov	Corp	Com	Opt	FX	CDS	All
LBC	1.57	−5.14	1.06	5.29	6.04	4.10	1.97	3.78
	(1.06)	(−0.42)	(2.09)	(2.00)	(2.65)	(3.43)	(4.36)	(2.94)
Market	−0.29	11.61	0.53	1.59	−1.24	0.84	0.07	1.94
	(−0.12)	(0.50)	(0.89)	(0.55)	(−1.30)	(0.78)	(0.15)	(0.63)
Constant	0.02	0.03	0.01	−0.01	0.05	−0.01	0.00	0.00
	(0.84)	(0.75)	(5.00)	(−0.57)	(1.24)	(−0.50)	(−2.27)	(−0.21)
R^2	0.36	0.89	0.61	0.27	0.99	0.85	0.92	0.50
N	25	6	20	23	18	12	20	124
T	67	60	63	67	63	55	47	67

Panel B: Quarterly Horserace with HKM Portfolios

	Equity	Sov	Corp	Com	Opt	FX	CDS	All
LBC	1.19	−3.17	0.58	4.62	6.14	4.45	1.64	3.29
	(1.08)	(−0.68)	(1.21)	(1.97)	(2.92)	(3.47)	(4.03)	(2.07)
HKM	1.10	4.18	1.24	2.40	0.22	1.43	0.50	2.78
	(0.52)	(0.64)	(1.84)	(0.91)	(0.65)	(1.34)	(1.23)	(1.25)
Market	−0.01	4.78	−0.12	1.60	−1.25	0.90	0.00	1.73
	(0.00)	(0.70)	(−0.17)	(0.50)	(−1.15)	(0.78)	(0.01)	(0.57)
Constant	0.02	0.02	0.01	0.00	0.04	−0.01	0.00	0.00
	(0.75)	(1.45)	(3.47)	(−0.26)	(1.12)	(−0.40)	(−2.11)	(0.05)
R^2	0.36	0.91	0.68	0.28	1.00	0.86	0.92	0.56
N	25	6	20	23	18	12	20	124
T	67	60	63	67	63	55	47	67

This table reports annualized market prices of risk (in p.p.) for one standard deviation difference in time-series exposure towards LBC, the capital risk factor of HKM and the market return when we use the original portfolios of HKM. The estimates result from Fama-MacBeth regressions of quarterly portfolio returns from February 1996 to December 2012, where GMM-adjusted t-statistics are presented in parentheses. Panel A includes LBC, the market return and a cross-sectional intercept, while we add the capital risk factor of HKM in Panel B. R^2 denotes the cross-sectional R-squared, N reports the number of cross-sectional portfolios within an asset class, and T is the number of observations.

Table B.2: Market Price of Risk Excluding the Great Recession

Panel A: Quarterly

	Equity	Sov	Corp	Com	Opt	FX	CDS	All
LBC	0.84	−0.03	0.98	9.11	5.95	1.60	1.03	5.87
	(0.69)	(−0.10)	(1.33)	(2.36)	(4.20)	(2.79)	(3.00)	(2.25)
Market	−0.48	0.28	0.23	0.04	−0.16	0.70	1.10	4.11
	(−0.27)	(0.70)	(0.19)	(0.02)	(−0.56)	(0.99)	(3.32)	(1.41)
Constant	0.03	0.00	0.01	0.01	0.04	−0.01	0.00	0.00
	(2.23)	(1.03)	(3.25)	(1.05)	(1.87)	(−2.07)	(−3.55)	(0.25)
R^2	0.37	0.67	0.94	0.72	1.00	0.16	0.92	0.72
N	25	6	7	24	18	12	20	112
T	86	67	83	86	86	86	40	86

Panel B: Monthly

	Equity	Sov	Corp	Com	Opt	FX	CDS	All
LBC	−0.22	−0.24	1.36	4.61	5.54	3.16	1.43	3.95
	(−0.21)	(−0.65)	(1.31)	(1.77)	(3.83)	(1.33)	(2.17)	(2.61)
Market	−1.00	0.42	−0.37	−2.19	−0.23	−1.88	0.43	4.36
	(−0.71)	(0.70)	(−0.39)	(−0.90)	(−0.85)	(−1.44)	(1.05)	(1.60)
Constant	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00
	(3.22)	(1.11)	(3.55)	(1.78)	(2.07)	(−0.31)	(−3.62)	(−0.02)
KZ-p	0.04	0.06	0.02	0.51	0.00	0.63	0.12	0.03
R^2	0.18	0.73	0.93	0.33	1.00	0.59	0.94	0.47
N	25	6	7	24	18	12	20	112
T	262	204	251	262	262	262	124	262

Panel C: Quarterly HKM portfolios

	Equity	Sov	Corp	Com	Opt	FX	CDS	All
LBC	2.32	−2.93	0.57	5.63	5.63	3.97	0.93	4.66
	(1.14)	(−0.48)	(1.33)	(1.48)	(2.78)	(2.88)	(2.97)	(2.88)
Market	−0.01	10.12	1.30	2.34	−0.65	0.50	1.22	3.47
	(0.00)	(1.12)	(2.09)	(0.60)	(−1.04)	(0.34)	(3.83)	(1.02)
Constant	0.02	0.02	0.01	0.00	0.05	0.00	0.00	0.00
	(1.08)	(0.78)	(5.23)	(−0.09)	(1.22)	(−0.18)	(−3.83)	(0.07)
R^2	0.50	0.90	0.61	0.24	1.00	0.79	0.92	0.62
N	25	6	20	23	18	12	20	124
T	60	53	56	60	56	48	40	60

This table reports annualized market prices of risk (in p.p.) for one standard deviation difference in time-series exposure towards LBC and the market return when we disregard portfolio returns in the Great Recession. Therefore, we exclude portfolio returns from December 2007 to June 2009 according to the NBER recession indicators. The estimates result from Fama-MacBeth regressions of portfolio returns from February 1996 to June 2019, where GMM-adjusted t-statistics are presented in parentheses. All panels include LBC, the market return as well as a cross-sectional intercept. Panel A and Panel B report estimates for our portfolios from 1996 to 2019, while Panel C presents results from 1996 to 2012 with the original portfolios of HKM. KZ-p depicts the p-value of Kleibergen and Zhan (2020)'s F-test with the null hypothesis of misspecified risk premia. R^2 denotes the cross-sectional R-squared, N reports the number of cross-sectional portfolios within an asset class, and T is the number of observations.

Table B.3: Market Price of Risk for Equally-Weighted LBC

Panel A: Quarterly

	Equity	Sov	Corp	Com	Opt	FX	CDS	All
LBC	0.76	0.14	0.89	7.74	5.52	1.02	2.00	4.70
	(0.75)	(0.27)	(1.32)	(2.20)	(3.68)	(2.44)	(3.92)	(1.85)
Market	−0.49	0.32	−0.02	0.49	−0.38	1.80	−0.05	3.13
	(−0.30)	(0.80)	(−0.02)	(0.26)	(−0.73)	(2.41)	(−0.10)	(1.05)
Constant	0.03	0.00	0.01	0.01	0.03	−0.01	0.00	0.00
	(1.70)	(0.90)	(2.64)	(0.92)	(1.81)	(−2.34)	(−2.01)	(0.07)
R^2	0.32	0.91	0.83	0.59	1.00	0.13	0.90	0.62
N	25	6	7	24	18	12	20	112
T	93	74	90	93	93	93	47	93

Panel B: Monthly

	Equity	Sov	Corp	Com	Opt	FX	CDS	All
LBC	0.23	−0.23	0.98	4.33	5.24	2.51	2.30	3.59
	(0.32)	(−0.68)	(1.26)	(2.00)	(3.56)	(1.40)	(3.57)	(2.04)
Market	−0.55	0.51	−0.29	−1.12	−0.50	−1.75	−0.40	3.29
	(−0.43)	(0.97)	(−0.28)	(−0.61)	(−1.20)	(−1.62)	(−1.09)	(1.30)
Constant	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00
	(1.94)	(1.26)	(3.00)	(1.65)	(2.23)	(0.49)	(−3.35)	(−0.15)
KZ-p	0.01	0.03	0.00	0.36	0.00	0.56	0.00	0.02
R^2	0.13	0.80	0.75	0.28	1.00	0.49	0.94	0.44
N	25	6	7	24	18	12	20	112
T	281	223	270	281	281	281	143	281

This table reports annualized market prices of risk (in p.p.) for one standard deviation difference in time-series exposure towards an equally-weighted LBC and the market return. The estimates result from Fama-MacBeth regressions of quarterly (Panel A) and monthly (Panel B) portfolio returns from February 1996 to June 2019, where GMM-adjusted t-statistics are presented in parentheses. All panels include a cross-sectional intercept. In contrast to the original definition in (4), we weight each pseudo-FI equally in this estimation. KZ-p depicts the p-value of Kleibergen and Zhan (2020)'s F-test with the null hypothesis of misspecified risk premia. R^2 denotes the cross-sectional R-squared, N reports the number of cross-sectional portfolios within an asset class, and T is the number of observations.

Table B.4: Horseraces with Intermediary Risk Factors

Panel A: AEM

	Equity	Sov	Corp	Com	Opt	FX	CDS	All
LBC	0.91	−0.04	0.97	7.63	5.47	1.39	0.82	5.07
	(0.89)	(−0.06)	(1.14)	(2.67)	(2.98)	(1.83)	(1.72)	(2.60)
AEM	0.03	−0.24	0.55	−2.95	0.65	−2.41	−1.27	−1.17
	(0.03)	(−0.43)	(0.56)	(−1.13)	(0.38)	(−1.58)	(−3.32)	(−0.55)
Market	−0.71	0.16	−0.49	0.55	−0.66	3.32	0.87	3.12
	(−0.45)	(0.41)	(−0.34)	(0.28)	(−0.80)	(1.81)	(2.42)	(1.02)
Constant	0.03	0.00	0.01	0.01	0.04	−0.01	0.00	0.00
	(1.82)	(0.76)	(2.37)	(1.10)	(1.63)	(−1.41)	(−1.17)	(0.10)
R^2	0.39	0.83	0.90	0.69	1.00	0.47	0.97	0.68
N	25	6	7	24	18	12	20	112
T	86	67	83	86	86	86	47	86

Panel B: Intermediary Equity

	Equity	Sov	Corp	Com	Opt	FX	CDS	All
LBC	0.70	0.02	0.92	6.54	5.13	1.88	1.99	4.63
	(0.83)	(0.02)	(1.51)	(2.13)	(3.12)	(1.70)	(4.28)	(2.43)
Int. Equity	−0.64	0.62	0.02	−2.24	0.28	4.00	−0.06	1.09
	(−0.45)	(0.60)	(0.02)	(−0.44)	(0.29)	(2.47)	(−0.17)	(0.36)
Market	−1.06	0.74	−0.06	0.50	−0.27	0.90	0.07	3.64
	(−0.47)	(0.74)	(−0.10)	(0.13)	(−0.61)	(0.49)	(0.21)	(1.17)
Constant	0.03	0.00	0.01	0.01	0.03	−0.02	0.00	0.00
	(1.95)	(0.82)	(1.88)	(1.14)	(1.74)	(−1.08)	(−1.99)	(0.12)
R^2	0.34	0.99	0.85	0.80	1.00	0.75	0.92	0.73
N	25	6	7	24	18	12	20	112
T	93	74	90	93	93	93	47	93

This table reports annualized market prices of risk (in p.p.) for one standard deviation difference in time-series exposure towards LBC, the market return and other intermediary risk factors. The estimates result from Fama-MacBeth regressions of quarterly portfolio returns from February 1996 to June 2019, where GMM-adjusted t-statistics are presented in parentheses. Both panels include LBC, the market return as well as a cross-sectional intercept. Additionally, Panel A includes the change in the risk factor of Adrian, Etula, and Muir (2014), while Panel B reports estimates for the value-weighted stock returns of NY Fed Primary Dealers. R^2 denotes the cross-sectional R-squared, N reports the number of cross-sectional portfolios within an asset class, and T is the number of observations.

Table B.5: Horseraces with Non-Intermediary Risk Factors

Panel A: cay

	Equity	Sov	Corp	Com	Opt	FX	CDS	All
LBC	0.41	0.13	1.00	8.29	5.36	3.47	2.10	4.87
	(0.55)	(0.23)	(1.53)	(2.34)	(3.55)	(2.72)	(4.17)	(2.03)
cay	0.67	−0.11	0.17	0.48	0.08	−2.71	0.20	0.01
	(0.91)	(−0.40)	(0.72)	(0.17)	(0.30)	(−1.89)	(0.53)	(0.00)
Market	−0.48	0.27	−0.01	−0.21	−0.15	1.42	0.11	2.96
	(−0.37)	(0.84)	(−0.01)	(−0.11)	(−0.17)	(1.49)	(0.30)	(1.02)
Constant	0.03	0.00	0.01	0.01	0.02	−0.02	0.00	0.00
	(1.99)	(0.99)	(2.36)	(0.96)	(0.94)	(−1.85)	(−2.42)	(0.08)
R^2	0.39	0.90	0.87	0.69	1.00	0.36	0.92	0.66
N	25	6	7	24	18	12	20	112
T	93	74	90	93	93	93	47	93

Panel B: Risk Aversion

	Equity	Sov	Corp	Com	Opt	FX	CDS	All
LBC	1.08	−0.31	1.49	6.46	5.09	2.28	2.03	4.76
	(1.00)	(−0.35)	(1.76)	(2.22)	(3.30)	(3.65)	(3.96)	(2.42)
RA	0.17	0.17	0.19	3.16	−0.56	−0.15	−0.10	0.78
	(0.23)	(0.15)	(0.37)	(1.06)	(−1.50)	(−0.35)	(−0.44)	(0.43)
Market	−0.98	0.39	−0.36	0.39	−0.39	1.34	−0.12	3.09
	(−0.52)	(0.47)	(−0.28)	(0.19)	(−0.79)	(1.72)	(−0.28)	(1.02)
Constant	0.03	0.00	0.01	0.01	0.03	−0.01	0.00	0.00
	(1.71)	(0.71)	(1.82)	(1.21)	(1.80)	(−2.20)	(−1.99)	(0.20)
R^2	0.45	0.99	0.90	0.72	1.00	0.39	0.92	0.69
N	25	6	7	24	18	12	20	112
T	83	64	80	83	83	83	47	83

This table reports annualized market prices of risk (in p.p.) for one standard deviation difference in time-series exposure towards LBC, the market return and other non-intermediary risk factors. The estimates result from Fama-MacBeth regressions of quarterly portfolio returns from February 1996 to June 2019, where GMM-adjusted t-statistics are presented in parentheses. Both panels include LBC, the market return as well as a cross-sectional intercept. Panel A includes updated data of cay from Lettau and Ludvigson (2001) and Panel B presents results when controlling for the Risk Aversion measure of Bekaert, Engstrom, and Xu (2021). R^2 denotes the cross-sectional R-squared, N reports the number of cross-sectional portfolios within an asset class, and T is the number of observations.