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Financial contagion risk and the stochastic discount factor

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ABSTRACT

I provide evidence that financial contagion risk is an important source of the equity risk premium. Banks' contributions to aggregate financial contagion are estimated in a state space framework and linked to systemic risk. Greater bank connectedness today leads to increased systemic risk 3–12 months later. More contagious banks earn significantly greater risk-adjusted returns than less contagious ones and the tradable high contagion-minus-low contagion bank portfolio is priced in the cross-section of stock returns. Stocks that co-move more strongly with contagious banks have greater expected returns. These results are robust to factor model specification, test assets, and time period considered.

1. Introduction

Financial intermediaries serve a special role in the economy through investing on households' behalf and by issuing credit, both of which can affect the aggregate consumption set. As financial intermediaries experience negative shocks, household wealth decreases (Allen et al., 2012) and credit may be constrained (Duchin et al., 2010; Ivashina and Scharfstein, 2010). In the aggregate, this diminished wealth and credit constraint leads to levels of consumption and consumption responsiveness being diminished (Berger and Vavra, 2015; Favara and Imbs, 2015). Conversely, as financial intermediaries experience positive shocks, household wealth increases, credit availability is liberated and consumption increases. Financial intermediaries' propensity to experience positive and negative shocks contemporaneously shocks aggregate consumption possibilities in the same direction. Modern asset pricing theory proposes that risk-averse investors with concave utility require a greater return on securities whose returns experience greater covariation with contagious intermediaries since these securities have high payoffs in good times and low payoffs in bad times. I argue that financial contagion risk is not diversifiable and that it affects the equity risk premium.

Alternatively, since intermediaries serve as agents of households to invest on their behalf, it could be that intermediaries' marginal utility of wealth and stochastic discount factor (SDF) prices securities as proposed in Cochrane (2011). In the case of an intermediary SDF, increased financial contagion leads to increased interbank funding illiquidity, such as observed in Schnabl (2012). A severe enough decrease in funding liquidity can result in market freezes (Acharya et al., 2011) or fire sales (Jotikasthira et al., 2012; Shleifer and Vishny, 1992). In each of these cases, asset payoffs covary negatively with the intermediary's marginal utility of wealth. It follows that with an intermediary SDF, intermediaries also require a greater expected return for holding securities that experience greater covariation with more contagious intermediaries.

My paper contributes to the new and growing area of financial intermediary asset pricing by showing that financial contagion risk enters the SDF. I define financial contagion in the spirit of Eun and Shim (1989), Bekaert et al. (2005), Bekaert et al. (2014), and the broader contagion literature to be the covariation in bank stock returns in excess of what is predicted by common systematic risk movements. As an innovation to the contagion methodology literature, I use state space methods to estimate bank excess covariations and I scale excess bank return covariances by the return variance of the bank portfolio to give estimates of the contribution of each bank to total financial contagion as well as to provide an estimate of the fraction of the bank portfolio's return variance that is attributable to financial contagion.[2] This type of variance decomposition to measure contagion is similar in spirit to the variance

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[2] Similar measures, although with the aim of measuring downside systemic risk specifically, include conditional value-at-risk (*CoVaR*)

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decomposition methodology of Diebold and Yı lmaz (2014). In addition, this approach gives a time-varying measure of the importance of financial contagion risk, relative to common risks, at any given time.

While the extant literature generally treats systemic risk and contagion risk separately, one can imagine that there is a symbiotic relationship between the two. In the presence of endogenously determined capital and credit constraints, non-systemic shocks can propagate through the financial system and ultimately become systemic events affecting both institutions and asset prices (Elliot et al., 2014; Holmstrom and Tirole, 1996; 1997; Kiyotaki and Moore, 1997; 2002; Longstaff and Wang, 2012; Shenoy and Williams, 2017). If fire sales or market freezes result from the propagation of shocks, then the resulting change in the aggregate elasticity of intertemporal substitution (EIS) affects asset prices sparking a self-fulling cycle.[3]

Since financial contagion levels need to affect the growth of investors' marginal utility for financial contagion to be priced, financial contagion is linked to systematic and systemic risks. I find that estimates of aggregate financial contagion are pro-cyclical with banks becoming more connected when risk-aversion is lower and disentangling as risk-aversion increases. An increase in financial contagion is significantly contemporaneously associated with higher market returns, higher cash flow news, lower discount rate news, and a lower *MES*.[4] However, an increase in financial contagion today significantly leads to lower market returns, lower cash flows, higher *MES*, and higher *CoVaR* 3 to 12 months in the future. Conversely, changes in the level of financial contagion are positively related to the past 9 months of market returns, positively related to the last 10 months of cash flow news, negatively related to discount rate news over the last 4 months, and negatively related to the past 10 months of *MES*. These results provide evidence that financial contagion affects investors' marginal utility in important ways. Further, the results show that levels of systemic risk and levels of financial contagion make up a reinforcing cycle.

Since increases in financial contagion today affect growth in marginal utility in consumption negatively today and positively in the future, investors' degree of time preference determines the price of contagion risk. A representative investor with Epstein and Zin (1989) preferences that is more concerned with the present than with the future implies a positive price of contagion risk whereas a representative investor that is more concerned with the future than with the present implies a negative price of contagion risk. I find a positive price of contagion risk which implies that investor's have a short-term time preference. Other recent studies including van Binsbergen et al. (2012), van Binsbergen et al. (2013), and Belo et al. (2015) find evidence that investor' have short-term time preferences by looking at the term structure of dividend strips.

When sorted into log value-weighted terciles, the tercile with high contagion banks outperforms the tercile with low contagion banks by an annualized mean return of 4.9%. Factor regressions show that the mean annualized abnormal return for the high contagion-minus-low contagion bank portfolio is 2.4% and persists after accounting for standard asset pricing factors. Additionally, a positive relationship cannot be rejected between the bank portfolio contagion level and the bank portfolio mean return with investors requiring an increase in mean return of 70 basis points per annum to hold an adjacent decile of bank stocks with a higher contagion risk.

I form the financial contagion risk factor portfolio (HCMLC) by buying the tercile of bank stocks that contribute the most to financial contagion and by selling the tercile of bank stocks that contribute the least to financial contagion. The null hypothesis of no relationship between a stock portfolio's HCMLC beta and its mean return is rejected. Investors require an increase in expected return of 50 basis points per annum, relative to what is predicted by the Fama and French (1993) model augmented with the Carhart (1997) momentum factor and the Pástor and Stambaugh (2003) liquidity factor, to hold an adjacent common stock decile with a higher HCMLC beta. Standard asset pricing tests reveal that the annualized HCMLC risk premium from firm-level (Fama and MacBeth, 1973) regressions is 3.3% and that it is 4.5% when test portfolios sorted on size, book-to-market (B/M), industry, and momentum are used.

1.1. Related literature

My paper is related to the growing body of financial intermediary asset pricing. He and Krishnamurthy (2013) provides a theoretical basis for a financial intermediary SDF. Adrian et al. (2014) empirically tests for an intermediary SDF and they find that a single-factor model, using broker-dealer leverage as the only factor, prices portfolios sorted on size, B/M, and momentum better than the Carhart four-factor model. I find that the HCMLC factor alone similarly prices test portfolios as well as the FFCPS model in full-sample cross-sectional tests. My results provide evidence of an alternative avenue through which financial intermediary risk enters the SDF. While Adrian et al. (2014) focus on broker-dealer leverage as a proxy for intermediary SDF, I focus on how financial contagion risk enters the SDF. My bank-based factor has the advantage that it can be observed at a higher frequency while broker-dealer leverage observations are restricted to the quarterly frequency and my paper further adds to the literature by allowing bank returns to directly enter the SDF.

Intermediary leverage and financial contagion need not be mutually exclusive and are in fact often considered connected. In the models of Allen and Gale (2000) and Leitner (2005), financial contagion results when interbank defaults occur in the presence of sufficiently high interbank leverage. Financial contagion, however, need not be correlated with intermediary leverage levels. The correlation between the HCMLC factor of the present paper and the broker-dealer leverage factor of Adrian et al. (2014) is 0.083 which indicates that financial contagion risk is an alternative distinct risk. Alternative mechanisms of financial contagion in the literature include heterogeneously informed traders (King and Wadhwani, 1990; Yuan, 2005; Pasquariello, 2007), portfolio re-balancing (Fleming et al., 1998), "flights to quality" (Kyle and Xiong, 2001; Kodres and Pritsker, 2002), liquidity shocks (Diamond and Rajan, 2001; 2005; Brusco and Castiglionesi, 2007) and through a collateral channel (Benmelech and Bergman, 2011).

The remainder of the paper is organized as follows. Section 2 discusses the methodology used to estimate financial contagion. Section 3 relates financial contagion to arbitrage pricing theory. Section 4 discusses the data. Section 5 presents financial contagion estimates. Section 6 and Section 7 present the main asset pricing results. Section 8 contains concluding remarks.

2. Financial contagion methodology

I define financial contagion in the spirit of the broader contagion literature to be the covariance between bank returns that is in

(Adrian and Brunnermeier, 2016), marginal expected shortfall (*MES*) (Acharya et al., 2010), and the connectedness measures of Billio et al. (2012).

[3] Vissing-Jørgensen (2002) also shows that the EIS varies for individuals dependent on if the individual is a risky asset holder or not.

[4] Since *MES* and *CoVaR* are measures of left tail risk, they are multiplied by -1 in the present paper so that increases in *MES* and *CoVaR* indicate an increase in systemic risk.

excess of what is predicted by commonly shared systematic risks. Identifying financial contagion is a three step procedure and the resulting financial contagion measure is a variance decomposition of bank returns (similar in spirit to Diebold and Yı lmaz (2014)). In the first step, the component of observed bank returns that is generated by common systematic risk exposure is removed. Let there be N stocks that make up the bank portfolio and assume that bank stock returns are generated by the following k-factor model:

$$r_{i,t} = \alpha_{i,t} + \boldsymbol{f}_t' \boldsymbol{\beta}_{\mathbf{i,t}} + e_{i,t}, \tag{2.1}$$

$$\begin{bmatrix} \alpha_{i,t} \\ \boldsymbol{\beta}_{i,t} \end{bmatrix} = \begin{bmatrix} \rho_{i,\alpha} & \mathbf{0}' \\ \mathbf{0} & \mathbf{R}_i \end{bmatrix} \begin{bmatrix} \alpha_{i,t-1} \\ \boldsymbol{\beta}_{i,t-1} \end{bmatrix} + \boldsymbol{\eta}_{i,t},$$

$$i \in \{1, 2, ..., N\}, \quad t \in \{1, 2, \dots, T_i\}, \tag{2.2}$$

where $r_{i,t}$ is the observed stock return at time t for bank i, $\boldsymbol{f}_t = (f_1, f_2, \dots, f_k)_t'$ is a vector of k observed factors at time t, $\boldsymbol{\beta}_{i,t} = \left(\beta_{i,1}, \beta_{i,2}, \dots, \beta_{i,k}\right)_t'$ is the time-varying vector of k factor loadings, $\alpha_{i,t}$ is a time-varying intercept term, $\mathbf{0}$ is the $(k \times 1)$ zero vector, $\rho_{i,\alpha}$ is the autoregressive (AR) parameter for α_i and $\mathbf{R}_i$ is the $(k \times k)$ diagonal matrix of factor AR parameters for bank i. $e_{i,t}$ is the bank-specific shock, which is orthogonal to the factors and is distributed $e_{i,t} \sim N\left(0, \sigma_{i,t}^2\right)$. The covariance matrix of residuals across financial institutions may not be diagonal. Non-diagonal elements that are not equal to zero represent contagious bank covariances.

Eq. (2.1), as it is written, allows the model parameter values to change over time. The transition equation of coefficients is given in Eq. (2.2). $\boldsymbol{\eta}_{i,t}$ is a $((k+1) \times 1)$ vector of coefficient innovations with $e_{i,t}$ and $\boldsymbol{\eta}_{i,t}$ being uncorrelated.[5] $\boldsymbol{\Sigma}_{i,\eta}$ is a $((k+1) \times (k+1))$ diagonal matrix containing the coefficient innovation variances which imposes that alphas and factor loadings follow uncorrelated AR(1) processes. If $\boldsymbol{\Sigma}_{i,\eta} = \mathbf{0}$, then alphas and factor loadings are constant.

I use daily data to estimate Eq. (2.1) and (2.2) using the Kalman filter[6] to capture within-month variation in factor loadings, which (Patton and Ramadorai, 2013) show is important for modeling high-frequency risk exposure as well as to capture the autoregressive dynamics of the coefficient processes. Since the transition Eq. (2.2) allows for factor loadings to change daily (if $\boldsymbol{\eta} \neq \mathbf{0}$), the Kalman filter is ideal for filtering out common systematic risk exposure even when bank loadings on those risks change rapidly. Normality is assumed for the residual, in Eq. (2.1), so that the likelihood function is obtained for the Kalman filter. This assumption is not restrictive, however, since the residual can be non-normally distributed and a quasi-maximum likelihood estimator can be used for the Kalman filter.

Bank-specific shocks are the residual terms from Eq. (2.1):

$$\widehat{e}_{i,t} = r_{i,t} - \mathbf{E}(r_{i,t} | \mathcal{F}_{t-1}, \boldsymbol{f}_t) = r_{i,t} - \widehat{\alpha}_{i,t|t-1} - \boldsymbol{f}_t' \widehat{\boldsymbol{\beta}}_{i,t|t-1}, \tag{2.3}$$

where $\mathbf{E}(\cdot)$ is the mathematical expectations operator and $\mathcal{F}_{t-1}$ is the information set available at time $t-1$.

In the second step, the estimated residuals from Eq. (2.3) are regressed, without an intercept term, on returns of the value-weighted bank portfolio:

$$\hat{e}_{i,t} = z_{i,t} r_{I,t}^{(i)} + u_{i,t}, \tag{2.4}$$

$$z_{i,t} = \rho_{i,z} z_{i,t-1} + \omega_{i,t}, \tag{2.5}$$

$$r_{I,t}^{(i)} = \sum_{j \neq i} w_{j,t} r_{j,t}, \quad \sum_{j \neq i} w_{j,t} < 1. \tag{2.6}$$

Since the mean value for $\widehat{e}_{i,t}$ is equal to zero, coefficient estimates remain consistent when the intercept term is excluded in Eq. (2.4). $r_{I,t}^{(i)}$ is the return on the bank portfolio at time t excluding the contribution of bank i. Bank i's return contribution to the total bank portfolio return must be excluded to prevent bank i's idiosyncratic shock variance from being identified erroneously as financial contagion. $z_{i,t}$ is the scalar regression coefficient at time t for bank i which is restricted to vary with time following an AR(1) process with AR parameter $\rho_{i,z}$ and innovation $\omega_{i,t} \sim N(0, \Sigma_{i,\omega})$. If $\Sigma_{i,\omega} = 0$, then $z_{i,t}$ is constant across time. $z_{i,t}$ is allowed to be time-varying to capture time-varying financial contagion risks. $u_{i,t}$ is a random error term which is orthogonal to $\omega_{i,t}$ and is distributed as $u_{i,t} \sim N\left(0, \sigma_{u_i}^2\right)$.

Similarly to Eq. (2.1), I use the Kalman filtering methodology to estimate Eq. (2.4) to capture the dynamics of rapidly changing contagion risks and the autoregressive nature of those risks. The residual in Eq. (2.4) is assumed to be normally distributed to obtain the likelihood function for the Kalman filter and can be relieved to obtain the quasi-likelihood function. The resulting time-varying coefficients in Eq. (2.4) are filtered estimates of $z_{i,t}$, $\widehat{z}_{i,t|t}$, conditional on time t information.[7] Since $\widehat{e}_{i,t}$ is dependent on the coefficient estimates from Eq. (2.1), which are estimated with error, $\widehat{e}_{i,t}$ contains measurement error. This measurement error inflates the standard errors of $\widehat{z}_{i,t|t}$, but $\widehat{z}_{i,t|t}$ continues to be a consistent estimator of $z_{i,t}$. Consistency is the only property required for this methodology. From Eq. (2.4) it is not possible to distinguish between causality leading from the bank portfolio to the bank-specific shock of bank i from causality leading from bank i's idiosyncratic shock to the portfolio. However, knowing the direction of causality is not needed for my study.

The third step aggregates the coefficient estimates from Eq. (2.4) across banks at each date. Since Eq. (2.4) is a linear model, the projection theorem shows that the estimator of $\widehat{z}_{i,t|t}$ is:

$$\widehat{z}_{i,t|t} = \frac{\mathbf{E}_t\left(\widehat{e}_{i,t} r_{I,t}^{(i)} | \mathcal{F}_t\right)}{\mathbf{E}_t\left(\left(r_{I,t}^{(i)}\right)^2 | \mathcal{F}_t\right)}.$$

$\mathbf{E}_t\left(\left(r_{I,t}^{(i)}\right)^2 | \mathcal{F}_t\right) = \sigma_{r_I^{(i)},t}^2$ is the variance of bank portfolio returns at time t. Since $r_{I,t}^{(i)} = \sum_{j \neq i} w_{j,t} r_{j,t} = \sum_{j \neq i} w_{j,t}\left(\alpha_{j,t} + \boldsymbol{f}_t' \boldsymbol{\beta}_{j,t} + e_{j,t}\right)$ and following from the properties, $\mathbf{E}_t\left(\widehat{e}_{i,t} f_{l,t}\right) = 0$ for all i and $l \in (1, 2, \dots, k)$, and $\mathbf{E}_t\left(\widehat{e}_{i,t} \alpha_{j,t}\right) = 0$ $\forall i, j$, it follows that:

$$\widehat{z}_{i,t|t} = \frac{\sum_{j \neq i} w_{j,t} \mathbf{E}_t\left(\widehat{e}_{i,t} e_{j,t}\right)}{\sigma_{r_I^{(i)},t}^2}, \tag{2.7}$$

where w_j is the value weighting of bank j in the bank portfolio. $\alpha_{j,t}$, $\boldsymbol{\beta}_{j,t}$, and $e_{j,t}$ are the true intercept, true factor loadings, and true firm-specific shock for bank j at time t. Since $\textbf{plim}\widehat{e}_{i,t} = e_{i,t}$ and $\mathbf{E}_t\left(e_{i,t}\right) = 0$ $\forall i,t$, $\mathbf{E}_t\left(\widehat{e}_{i,t} e_{j,t}\right)$ is an estimate of the time-varying covariance between $e_{i,t}$ and $e_{j,t}$, $\widehat{\mathbf{CV}}_t\left(e_{i,t}, e_{j,t}\right)$. Note that the i' th bank's contribution to the portfolio's return is held out in Eq. (2.4) causing $r_{I,t}^{(i)}$ to vary for a given time t depending on which bank is the dependent variable. If, for all i, the $\widehat{z}_{i,t|t}$ estimates had common denominators, then the fraction of portfolio variance due to contagion could be estimated by taking the weighted summation $\sum_i w_{i,t} \widehat{z}_{i,t|t}$. However, since $r_{I,t}^{(i)}$ is different for each i, each $\sigma_{r_I^{(i)},t}^2$ is also different. Therefore, $\widehat{z}_{i,t|t}$ must be post-multiplied by

[5] While (Patton and Verardo, 2012) provide evidence that return shocks and beta shocks are correlated surrounding firms' quarterly earnings announcements, these are rare events and the present paper assumes that the two shocks are uncorrelated.

[6] A review of the Kalman filtering methodology can be found in Lütkepohl (2005).

[7] While standard errors for $\widehat{z}_{i,t|t}$ estimates are not presented, they have been estimated as well.

Table 1
Summary statistics. This table presents summary statistics for the daily sample of financial firms only in Panel A and the monthly CRSP sample of stocks in Panel B. PRICE is stock price, RET, is monthly stock total return (daily log total return in Panel A), MVE is market value of equity (in billions), BIR is the bank index return, $\widehat{z}_{t|t}$ is the coefficient estimate in Eq. (2.4), $FC_t^{(i)}$ is the contribution of bank i to financial contagion, FC_t is the estimate of the fraction of bank portfolio return variance attributable to financial contagion obtained from Eq. (2.8), and $\widehat{\sigma}^2_{r_I^{(i)},t}/\widehat{\sigma}^2_{r_I,t}$ is the ratio of the bank index return variance, excluding the return contribution of bank i, to the bank index return variance, including all banks. $\rho_{i,z}$, $\rho_{i,INT}$, $\rho_{i,MRKT}$, $\rho_{i,SMB}$, and $\rho_{i,HML}$ are the estimated AR transition parameters for z_i, α_i, $\beta_{i,MRKT}$, $\beta_{i,SMB}$, and $\beta_{i,HML}$, respectively. The bank sample in Panel A covers the period January 1, 1960 to December 31, 2012. Monthly stock and factor summary statistics are presented in panel B. VOL is monthly trading volume (in millions), MRKT is the excess market factor portfolio return, SMB is the small-minus-big factor portfolio return, HML is the high-minus-low factor portfolio return, MOM is the momentum factor portfolio return, LIQ is the tradable liquidity factor portfolio return, and HCMLC is the log value-weighted financial contagion factor portfolio return. The stock and factor sample in Panel B covers the period from January 1968 to December 2011.

	N	MEAN	SD	MEDIAN	Q25	Q75	MIN	MAX
Panel A: Bank Stock Summary Statistics (Daily Data)								
PRICE	5,783,608	20.453	19.521	16.375	9.725	26.000	0.010	710.750
RET	5,783,608	0.000	0.036	0.000	−0.010	0.010	−2.855	2.485
MVE	5,783,608	1.426	8.910	0.077	0.026	0.302	0.000	286.494
BIR	5,783,608	0.001	0.016	0.001	−0.006	0.007	−0.147	0.176
$\rho_{i,z}$	2309	0.486	0.781	0.990	0.047	0.994	−1.000	1.000
$\rho_{i,INT}$	2309	0.503	0.768	0.988	−0.114	0.990	−1.000	1.000
$\rho_{i,MRKT}$	2309	0.858	0.486	0.994	0.990	0.995	−1.000	1.000
$\rho_{i,SMB}$	2309	0.875	0.452	0.993	0.988	0.995	−1.000	1.000
$\rho_{i,HML}$	2309	0.710	0.669	0.987	0.974	0.992	−1.000	1.000
$\widehat{z}_{i,t\|t}$	5,783,608	0.100	0.656	0.053	−0.002	0.180	−583.632	874.914
$\widehat{\sigma}^2_{r_I^{(i)},t}/\widehat{\sigma}^2_{r_I,t}$	5,783,608	0.996	0.018	1.000	0.999	1.000	0.508	1.055
$FC_t^{(i)}$	5,783,608	0.000	0.002	0.000	0.000	0.000	−0.174	0.348
FC_t	5,783,608	0.205	0.079	0.191	0.152	0.246	−0.123	0.697
Panel B: Full Stock Sample and Factor Summary Statistics (Monthly Data)								
PRICE	2,501,921	24.814	767.104	12.813	5.625	24.250	0.016	141,600.000
RET	2,501,921	0.012	0.177	0.000	−0.067	0.072	−0.981	24.000
MVE	2,501,921	1.217	8.481	0.079	0.021	0.370	0.000	602.433
VOL	2,264,164	6.670	62.983	0.403	0.081	2.280	0.000	20,124.269
MRKT	2,501,921	0.055	0.560	0.104	−0.275	0.434	−2.789	1.932
SMB	2,501,921	0.018	0.396	−0.005	−0.208	0.247	−1.967	2.640
HML	2,501,921	0.047	0.374	0.046	−0.154	0.224	−1.512	1.661
MOM	2,501,921	0.090	0.542	0.101	−0.082	0.352	−4.169	2.207
LIQ	2,501,921	0.061	0.430	0.038	−0.191	0.300	−1.262	2.546
HCMLC	2,501,921	0.046	0.394	0.041	−0.200	0.274	−1.765	1.632

the variance ratio $\sigma^2_{r_I^{(i)},t}\left(\sigma^2_{r_I,t}\right)^{-1}$ prior to the summation. $\sigma^2_{r_I,t}$ is the bank portfolio return variance, including all banks. Since $\sigma^2_{r_I^{(i)},t}$ and $\sigma^2_{r_I,t}$ are unobservable and must be estimated, I use 90-day rolling historical variance estimators.[8] A variance estimator using trailing observations is used rather than a centered variance estimator so that variances can be estimated with an investor's current information set. Further, since the ratio $\sigma^2_{r_I^{(i)},t}\left(\sigma^2_{r_I,t}\right)^{-1}$ has a mean approximately equal to one (see the third from last row of Panel A of Table 1), the choice of variance estimator is largely irrelevant. Using a more sophisticated variance estimator increases the complexity and computational burden while adding little additional value.

Summing the product $w_{i,t}\widehat{z}_{i,t|t}\widehat{\sigma}^2_{r_I^{(i)},t}\left(\widehat{\sigma}^2_{r_I,t}\right)^{-1}$ over all i (banks) at each time t, and using Eq. (2.7), yields:

$$FC_t = \sum_i w_{i,t}\widehat{z}_{i,t|t}\widehat{\sigma}^2_{r_I^{(i)},t}\left(\widehat{\sigma}^2_{r_I,t}\right)^{-1} = \sum_i FC_t^{(i)} = \frac{C}{A+B+C},$$

$$A = \sum_{l=1}^{k}\widehat{\mathbf{V}}_t\left(f_{l,t}\right)\left(\sum_i\left(w_{i,t}\beta_{i,l,t}\right)^2 + 2\sum_{i,j:i<j}w_{i,t}w_{j,t}\beta_{i,l,t}\beta_{j,l,t}\right),$$

$$B = \sum_i w_{i,t}^2\widehat{\mathbf{V}}_t\left(e_{i,t}\right),$$

$$C = 2\sum_{i,j:i<j}w_{i,t}w_{j,t}\widehat{\mathbf{CV}}_t\left(e_{i,t},e_{j,t}\right). \tag{2.8}$$

Eq. (2.8) shows that at each time t FC_t is an estimator of the fraction of the bank portfolio return variance that is due to the covariances in bank-specific shocks, or financial contagion. Since FC_t is a ratio, it is bounded[9] between −1 and +1. The first term in the denominator of Eq. (2.8), A, is the contribution of common fundamental risks to the variance of the bank portfolio's returns. If the entire variation of bank returns can be explained by the factor model, then $FC_t = 0$. The second term of the denominator, B, is the contribution that banks' idiosyncratic risks contribute to the overall bank portfolio's return variance. The third term in the denominator, C, is the effect that financial contagion has on the bank portfolio's return variance. FC_t will only be non-zero if C is non-zero.

Forbes and Rigobon (2002) show that stochastic volatility often biases empirical contagion measures. Section A of the Internet Appendix presents a simulation model and simulation results, which show how the FC_t measure in Eq. (2.8) is affected by time-varying financial contagion, time-varying factor volatility, and time-varying bank idiosyncratic volatility. The simulation results provide evidence that FC_t is robustly able to track the true financial contagion level in the presence of time-varying financial contagion, time-varying factor volatility, and time-varying bank idiosyncratic volatility. Further, when there is only time-varying factor volatility and time-varying bank idiosyncratic volatility, FC_t remains consistent.

In the empirical results that follow, I estimate Eq. (2.1) with the Kalman filter within the Fama and French (1993) 3-factor model

[8] $\widehat{\sigma}^2_{r_I^{(i)},t} = \frac{1}{89}\sum_{k=t-90}^{t-1}\left(r_{I,k}^{(i)} - \widehat{\mu}_{r_I^{(i)},t}\right)^2$, $\widehat{\mu}_{r_I^{(i)},t} = \frac{1}{90}\sum_{k=t-90}^{t-1} r_{I,k}^{(i)}$, $\widehat{\sigma}^2_{r_I,t} = \frac{1}{89}\sum_{t-90}^{t-1}\left(r_{I,k} - \widehat{\mu}_{r_I,t}\right)^2$, $\widehat{\mu}_{r_I,t} = \frac{1}{90}\sum_{k=t-90}^{t-1} r_{I,k}$

[9] FC_t is bounded in practice, assuming well behaved empirical $\widehat{z}_{i,t|t}$ estimates.

(hereafter referred to as FF3F) presented below:

$$r^e_{i,t} = \alpha_{i,t} + \beta_{i,MRKT,t} r^e_{MRKT,t} + \beta_{i,SMB,t} r_{SMB,t} + \beta_{i,HML,t} r_{HML,t} + e_{i,t}, \tag{2.9}$$

where $r^e_{MRKT,t}$ is the daily excess return on the market portfolio, $r_{SMB,t}$ is the daily return on the small-minus-big portfolio, and $r_{HML,t}$ is the daily return on the high B/M-minus-low B/M portfolio. The residuals from the FF3F model are then used as the dependent variable in Eq. (2.4) and Eq. (2.4) is also estimated with the Kalman filter. Section D of the Internet Appendix shows that the asset pricing results that follow are robust to alternative factor model specifications for Eq. (2.9) including the CAPM, the Carhart (1997) 4-factor model, and the Fama and French (1993) 3-factor model augmented with a term structure variable.[10] As a simplifying estimation technique, in Section E of the Internet Appendix, I also present the results for when 90-day rolling ordinary least squares regressions are used to estimate Eq. (2.1) and (2.4) and I find similar results with the correlation between the two *FC* measures being 0.693.

3. Financial contagion and arbitrage pricing theory

In this section, I relate financial contagion to the arbitrage pricing theory of Ross (1976). Consider an example of financial contagion along the lines of Allen and Gale (2000). There are two states of the economy: a normal one which occurs with a probability of q and one with financial contagion which occurs with a probability of $1-q$. Assume that there is a set of banks $\mathcal{B}$ and that the loan supply $L_{i,t}$ of each bank $i \in \mathcal{B}$ is a function of their log market value of equity $L_{i,t}\left(p_{i,t}\right) = c_i + \ln(p_{i,t})$ for constants c_i. The constant c_i determines the point at which a bank's loan supply becomes negative (the point at which a bank begins demanding liquidity from other banks). At this threshold point, the bank portfolio's idiosyncratic shock no longer converge to 0. Therefore, loan supplies across banks are more highly correlated at lower bank share prices than at higher bank share prices and banks that have more correlated returns have more correlated loan supplies. Finally, assume for simplicity that firms have a constant demand for capital which may vary across firms.

In the normal state, there is no financial contagion and from Eq. (2.2) there exists a set of factor portfolios which span the set of well-diversified portfolios such that $r^e_{p,t} = \alpha_{p,t} + \boldsymbol{f}_t' \boldsymbol{\beta}_{p,t}$. If investors commonly know that this is the state, then financial contagion is not priced. Next, consider the state where financial contagion is present (for example, when banks do poorly). In this state, the aggregate loan supply of banks is affected and aggregate loan supply shocks have a lower tendency to cancel out as a result of their higher correlation in this state. Then, well-diversified portfolio returns become:

$$\begin{aligned} r^e_{p,t} &= \alpha_{p,t} + \boldsymbol{f}_t' \boldsymbol{\beta}_{p,t} + \sum_{j=1}^{M} \delta_{p,j,t} g_j \left(\sum_{i \in \mathcal{B}} \Delta L_{i,t} \right), \\ &= \alpha_{p,t} + \boldsymbol{f}_t' \boldsymbol{\beta}_{p,t} + \sum_{j=1}^{M} \delta_{p,j,t} g_j \left(\sum_{i \in \mathcal{B}} \Delta \ln\left(p_{i,t}\right) \right), \end{aligned} \tag{3.1}$$

where $g_j(\cdot)$ is a function which is increasing everywhere at a diminishing rate and passes through the origin such that $g_j(0) = 0$. $\delta_{p,j,t} = \mu_{p,j,t}/M$ are portfolio weights where M is the number of stocks held in the portfolio and $\mu_{p,j,t}$ are bounded constants such that $|\mu_{p,j,t}| < y < \infty$ for some y. Therefore, the final term in Eq. (3.1) which is an idiosyncratic shock term that converges to 0 in the normal state, no longer converges to 0 in the financial contagion state and is a systematic risk in nature. When the most contagious banks have negative returns, then the portfolio has negative returns and vice-versa for positive returns. As a result, if financial contagion is not controlled for, then the final term in Eq. (3.1) is erroneously observed as an inflation in the portfolio's alpha.

Investors do not know which state they are in. As a result, expected returns are a weighted expectation of the two states:

$$\begin{aligned} \mathbf{E}_t\left(r^e_{p,t+1}\right) &= \alpha_{t+1} + \boldsymbol{\beta}'_{p,t+1} \mathbf{E}_t\left(\boldsymbol{f}_{t+1}\right) \\ &\quad + (1-q) \sum_{j=1}^{M} \delta_{p,j,t+1} \mathbf{E}_t \left(g_j \left(\sum_{i \in \mathcal{B}} \Delta \ln\left(p_{i,t+1}\right) \right) \right). \end{aligned} \tag{3.2}$$

Eq. (3.2) can be put into a beta-model by taking a first-order Taylor series expansion of $g_j\left(\sum_{i\in\mathcal{B}} \Delta \ln\left(p_{i,t+1}\right)\right)$ around the point of $2\sum_{v\in\mathcal{A}} \Delta \ln\left(p_{v,t+1}\right)$ where $\mathcal{A}$ is some set of low contagion banks. The Taylor approximation yields:

$$\begin{aligned} & g_j \left(\sum_{i \in \mathcal{B}} \Delta \ln\left(p_{i,t+1}\right) \right) \\ & \approx g_j \left(2 \sum_{v \in \mathcal{A}} \Delta \ln\left(p_{v,t+1}\right) \right) + g_j' \left(\sum_{i \in \mathcal{B}} \Delta \ln\left(p_{i,t+1}\right) - 2 \sum_{v \in \mathcal{A}} \Delta \ln\left(p_{v,t+1}\right) \right) \\ & = g_j' r_{HCMLC,t+1}, \end{aligned} \tag{3.3}$$

where $g_j(2\sum_{v\in\mathcal{A}} \Delta \ln\left(p_{v,t+1}\right)) \approx 0$ and $r_{HCMLC,t+1} = \sum_{i\in\mathcal{A}^c} \Delta \ln p_{i,t+1} - \sum_{i\in\mathcal{A}} \Delta \ln p_{i,t+1}$. Note that the derivative $g_j'(r_{HCMLC})$ is stock j's beta with respect to $r_{HCMLC,t+1}$ which gives $g_j(r_{HCMLC}) \approx b_{j,HCMLC} r_{HCMLC}$. Therefore:

$$\begin{aligned} \mathbf{E}_t\left(r^e_{p,t+1}\right) &= \alpha_{p,t+1} + \boldsymbol{\beta}'_{p,t+1} \mathbf{E}_t\left(\boldsymbol{f}_{t+1}\right) + \frac{(1-q)}{M} \mathbf{E}_t\left(r_{HCMLC}\right) \sum_{j=1}^{M} \mu_j g_j' \\ &= \alpha_{p,t+1} + \boldsymbol{\beta}'_p \mathbf{E}_t\left(\boldsymbol{f}_{t+1}\right) + \beta_{p,HCMLC,t+1} \mathbf{E}_t\left(r_{HCMLC}\right), \end{aligned} \tag{3.4}$$

where $\beta_p = (1-q)\overline{\mu_j g_j'}$ and where the property that $\sum_{i=1}^{M} x_i = M\overline{x_i}$ has been used. If the financial contagion factor r_{HCMLC} is not included, then positive $\beta_{p,HCMLC}$ will have more positive observed alphas and negative $\beta_{p,HCMLC}$ portfolios will have more negative observed alphas.

4. Data and summary statistics

Daily bank stock prices from January 1, 1960 to December 31, 2012 are obtained from the CRSP daily stock file. All domestic banks (SIC codes from 6000 to 6199 and share code 10 or 11) and broker/dealers (SIC codes from 6200 to 6299 and share code 10 or 11) are initially included in the sample when their stock price first falls within a share price of \$5 and \$1,000.[11] To avoid survivorship bias, once a bank stock enters the sample it remains in the sample, regardless of share price. Bank stocks are dropped from the sample, if and when they are dropped from CRSP. There are 2388 banks in the sample with a total of 5,953,497 daily bank stock observations.

For the asset pricing tests, all common stocks (CRSP share code 10 or 11) within the CRSP universe are collected at a monthly frequency from January 1968 to December 2011 from the CRSP monthly stock file. A stock enters the sample once it has a share

[10] Ferson and Harvey (1999) show that the term structure has explanatory power for future asset returns.

[11] zero observations are dropped as the result of the \$1,000 price filter, and 1.76% of the initial sample observations are dropped as the result of the \$5 price filter.

price greater than \$5 and less than \$1,000.[12] Once a stock enters the sample it remains in the sample, regardless of share price and is removed from the sample if and when it is removed from CRSP to avoid survivorship bias. Daily bank stock returns are aggregated to monthly returns by converting daily returns into log returns, summing each month's log returns, and then converting the monthly aggregated log returns back into arithmetic returns by taking the exponential function of the aggregated log returns and subtracting 1. Factor data is obtained for the same period at a monthly frequency from two sources. Fama and French's three factors, as well as the momentum factor, are obtained from Kenneth French's website and the tradable liquidity factor is obtained from LŭbosPǎstor's website. Broker-dealer leverage factor data is obtained at the quarterly frequency from Tyler Muir's website for the Q1 1968 to Q4 2009 period.

Summary statistics for the sample of banks and for financial contagion estimates are presented in Panel A of Table 1. The mean bank market value of equity (MVE) is \$1.426 billion and bank MVEs are heavily skewed to the right. Banks' contributions to financial contagion, $FC_t^{(i)}$, are also heavily skewed to the right. Whereas the maximum contribution to financial contagion is 34.8 percentage points, the first and third quartiles are less than one basis point. The sample mean fraction of the observed bank portfolio return variance caused by financial contagion, $\overline{FC}$, is 20.5% and it has a sample standard deviation of 7.9%. FC_t obtains a maximum of 69.7% and a minimum of −12.3%. The mean AR transition parameters for Eq. (2.2) are 0.503, 0.858, 0.875, and 0.710 for alphas and factor loadings on MRKT, SMB, and HML, respectively. The mean AR transition parameter in Eq. (2.5) is 0.486 which provides evidence of the importance of using the Kalman filtering methodology to capture the autoregressive dynamics of contagion risks. The medians for each of these AR parameters are close to 1, indicating that AR parameters are heavily skewed to the left.

Panel B presents summary statistics for the stock and factor return sample. The mean stock price is \$24.814, the mean MVE is \$1.217 billion, and the mean monthly trading volume is 6.670 million shares. The mean annualized returns on the MRKT, SMB, HML, MOM, LIQ, and HCMLC (defined in Section 6) portfolios are, respectively, 5.5%, 1.8%, 4.7%, 9.0%, 6.1%, 4.9%, and 4.6%.

Fig. 1 plots the level of the value-weighted bank index in the top panel, the bank index return variance in the middle panel, and the aggregate bank firm-specific shock covariances in the bottom panel. January 1, 1960 is used as the base year for index level and the base index level is set equal to one. Estimated bank-specific shock covariances display a countercyclical nature. Covariances are high in periods of market stress and close to zero in times of relative market tranquility. During the 2007–'09 financial crises, covariances between bank stocks unexplainable by common systematic risks increases dramatically.

5. Financial contagion estimates

Fig. 2 plots the exponentially smoothed FC_t time series.[13] The smoothing parameter is 0.10 which corresponds to a half-life of approximately one week[14] (the results are relatively insensitive to the choice of smoothing parameter). Section B of the Internet Appendix contains the twenty banks that have the largest sample mean contributions to financial contagion, $\overline{FC}^{(i)}$, and the time se-

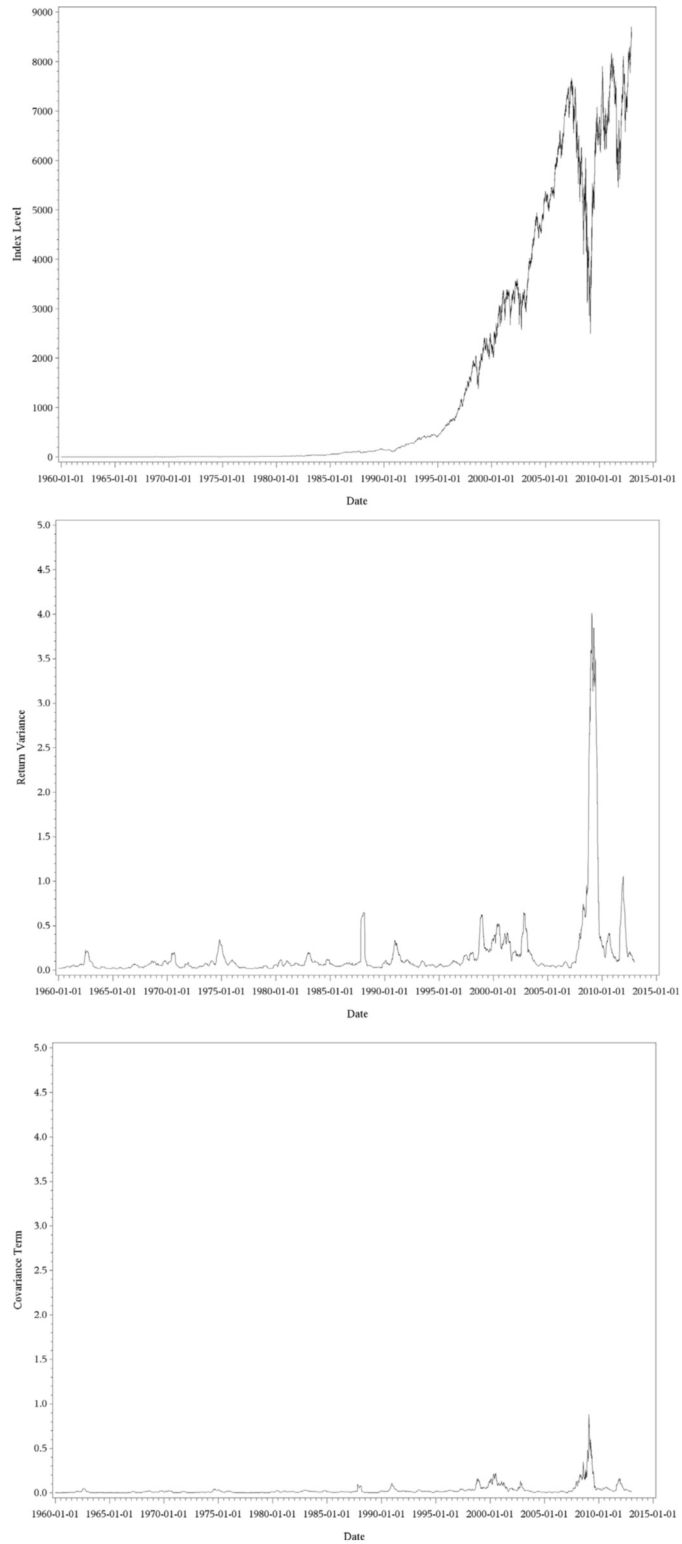

Fig. 1. Bank index time series. This figure plots the time series of the value-weighted bank index in the top panel, the time series of bank index return variance in the middle panel, and the time series of the covariance term of bank index return variance in the bottom panel. Time series in the middle and bottom panel are multiplied by 1000 for presentation. The bank index is constructed as the market-value weighted return of the bank sample. The base level for the bank index is set equal to one on January 1, 1960. Covariances, in the bottom panel, are obtained from $FC_t\hat{\sigma}^2_{r_{I,t}}$. FC_t is given by Eq. (2.8) and is smoothed for presentation using the exponential smoother given by:
$MA_t(FC) = 0.10FC_t + (1 - 0.10)MA_{t-1}(FC)$,
where the decay parameter 0.10 corresponds to a half-life of approximately 1 week. $\hat{\sigma}^2_{r_{I,t}}$ is the 90-day sample variance estimator for the value-weighted bank index returns.

[12] Less than 0.01% of the sample is dropped as a result of the \$1,000 price filter and 6.8% of the sample is dropped as a result of the \$5 price filter.

[13] Note that the aggregated FC_t time series is smoothed, not the $FC_t^{(i)}$ time series for banks.

[14] This smoothed time series is used for all tests that use the aggregate FC_t time series. The raw non-smoothed $FC_t^{(i)}$ time series is used when sorting banks into portfolios based on their contagion levels.

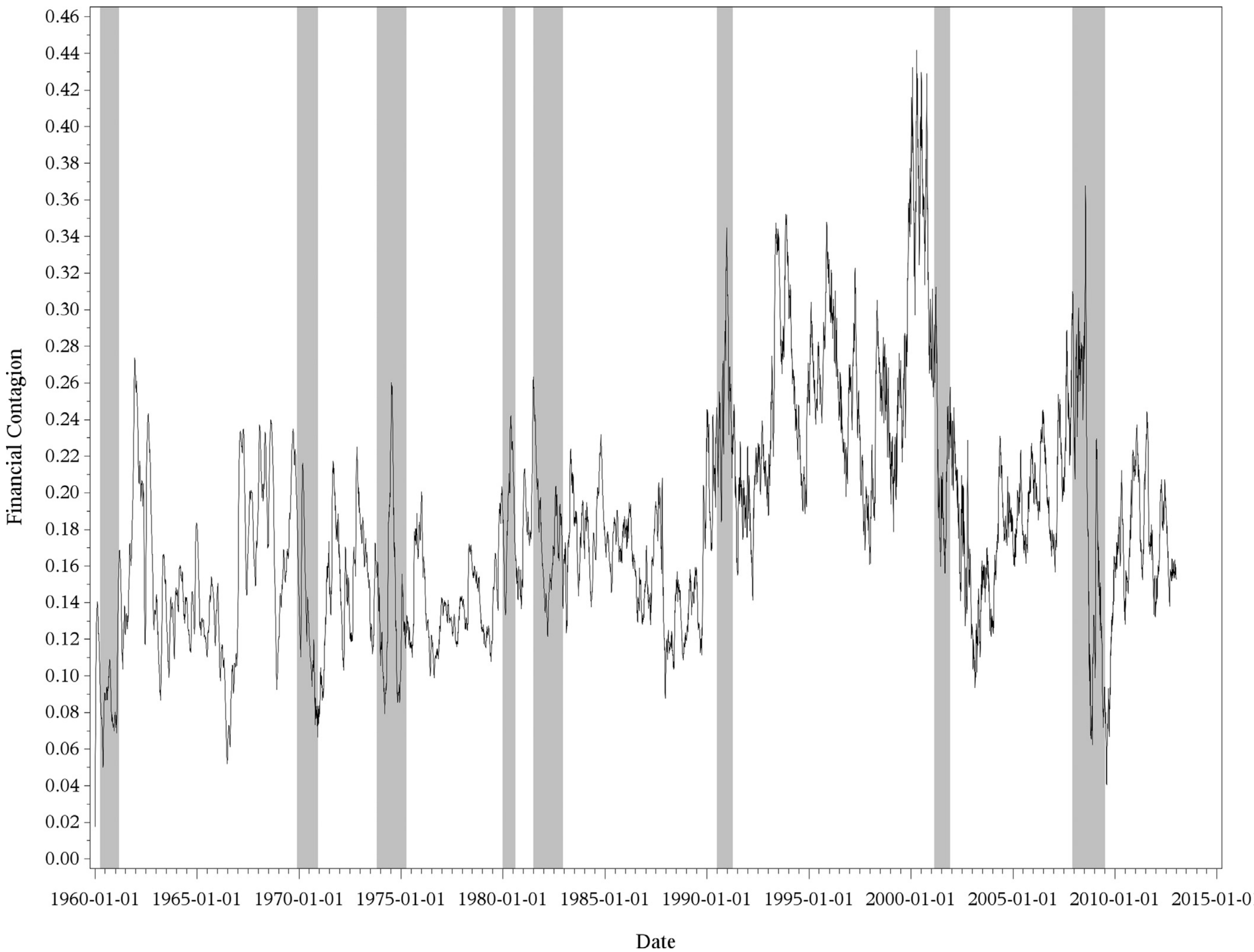

Fig. 2. Financial contagion time series. This figure plots the exponentially smoothed time series of the fraction of bank portfolio return variance attributable to financial contagion, FC_t, obtained from Eq. (2.8). The smoothing model is:
$MA_t(FC) = 0.10FC_t + (1 - 0.10)MA_{t-1}(FC)$,
where the decay parameter 0.10 corresponds to a half-life of approximately 1 week. Shaded regions are NBER recession dates.

ries of $FC^{(i)}$ for the most contagious banks in the sample. Graphically, the FC_t measure in Eq. (2.8) is formed by dividing the time series in the bottom panel of Fig. 1 by the time series in the middle panel of Fig. 1. FC_t is pro-cyclical with increases in bank inter-connectedness occurring in good times and disentangling in bad times. An examination of financial contagion during the 2007–2009 financial crisis is included in the Internet Appendix, in Section C.

The cross-sectional relationship between banks' mean contributions to aggregate financial contagion ($\overline{FC}_t^{(i)}$) and their respective mean annualized expected stock returns is plotted in Fig. 3. Generally, a positive (non-linear) relationship between a bank's financial contagion contribution and its expected return is observed. A bank's expected return is increasing in its contribution to financial contagion, but at a diminishing rate. This provides evidence that investor's view marginal increases in a bank's contagion level for less contagious banks as more risky than marginal increases in a more contagious bank's contagion level (where implicit government puts may be a factor). Interestingly, the least contagious banks have negative expected returns.

Since a factor needs to be a good measure of the growth of an investor's marginal utility, I link the level of financial contagion to future market returns, cash flow news, discount rate news, and measures of systemic risk (the marginal expected shortfall measure (*MES*) of Acharya et al. (2010) and the *CoVaR* measure of Adrian and Brunnermeier (2016)). The time series of *MES* and *CoVaR* which I construct and use are market-value weighted averages of *MES*s and *CoVaR*s of banks in the sample. Unexpected market returns, cash flow news, and discount rate news are measured using the methodology of Campbell and Shiller (1988).

Panel A of Table 2 presents the VAR results (using the Botshekan et al. (2012) VAR specification) using monthly market returns, the one-month risk-free rate, and the dividend yield on the S&P 500 as variables. Panel B of Table 2 presents autocorrelation coefficients of the first-difference $\triangle FC$ with the first-differences $\triangle N_{CF}$, $\triangle N_{DR}$, $\triangle FC\widehat{\sigma}^2_{r_t}$, $\triangle MES$, $\triangle CoVaR$, as well as with u_m (the residual term from the market return equation in the VAR). Time series used in Panel B are exponentially smoothed using a smoothing parameter of 0.206299 which corresponds to a half-life of approximately 3 months. Since *MES* and *CoVaR* are measures of left tail risk, they are multiplied by -1 so that increases in *MES* and *CoVaR* indicate an increase in systemic risk. Autocorrelation coefficients are presented as $\mathbf{COR}_j\left(\triangle FC_t, \triangle x_{t+j}\right)$. Bold-faced print denotes statistical significance at the 10% level or better. An increase in the level of *FC* is associated with significantly lower market returns starting 10 months in the future, lower cash flow news start-

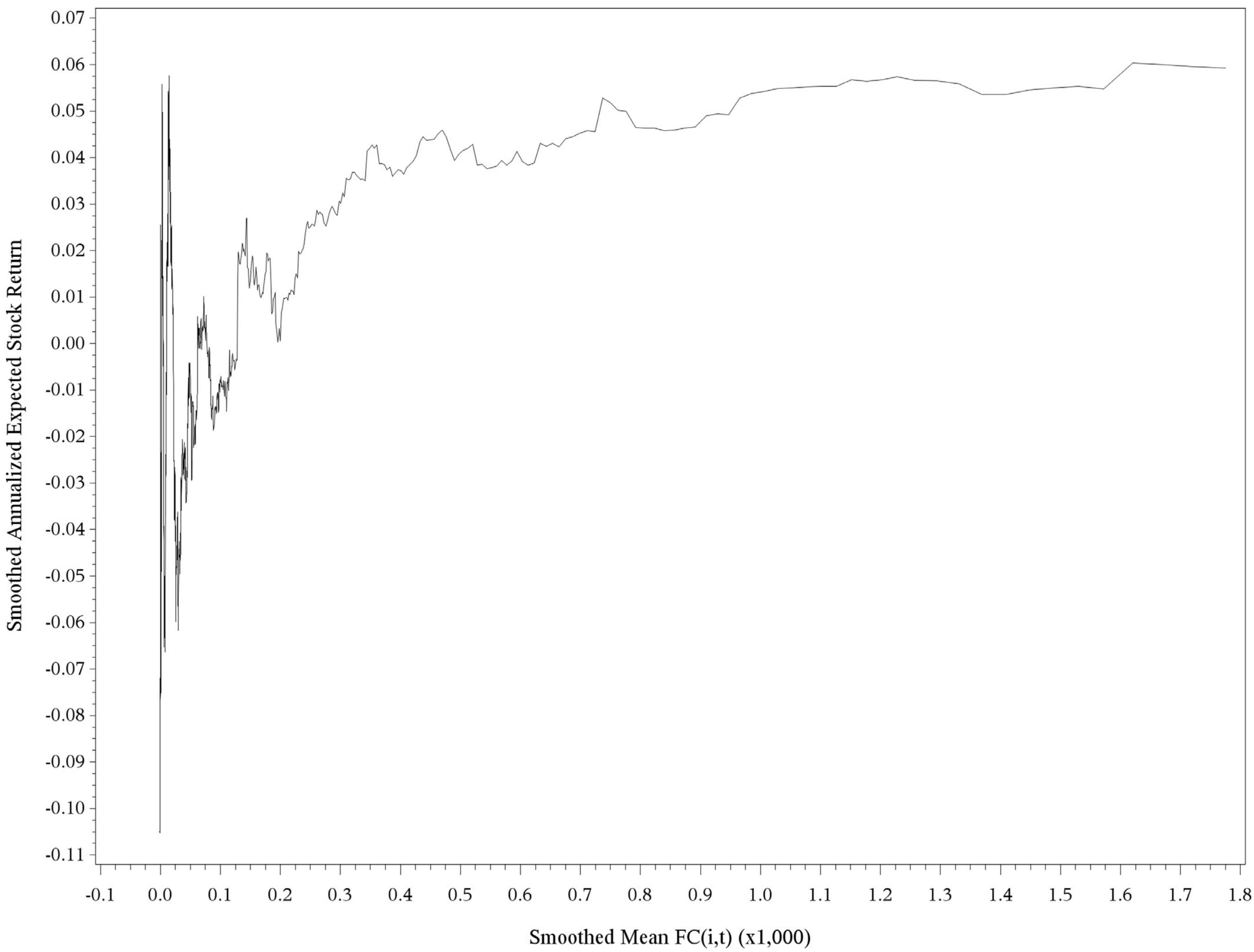

Fig. 3. Financial contagion and bank expected returns. This figure plots the smoothed cross-sectional relationship between a bank's mean contribution to aggregate financial contagion, $\overline{FC}_t^{(i)}$, and its annualized expected return (where the bar denotes the sample mean). The cross-sectional smoothing model is:

$$\widehat{x}_j = \sum_{m=-h}^{h} \frac{h+1-|m|}{(h+1)^2} x_{j+m},$$

where $x_j \in \{\overline{FC}_t^{(j)}, 12\bar{r}_{j,t}\}$ and the bandwidth parameter is $h = 100$ (4.37% of the cross-sectional sample of banks).

ing 10 months in the future, increasing *MES* starting 3 months in the future, and increasing *CoVaR* from 7 to 10 months in the future. These autocorrelation coefficients indicate that financial contagion is correlated with marginal utility growth and that an increase in the level of financial contagion leads to increased systemic risk in the following months.

Panel B also indicates that the present level of financial contagion is significantly associated with prior market returns, cash flow news, discount rate news, and levels of systemic risk. The level of financial contagion is positively related to the last 9 months of market returns, positively related to the past 10 months of cash flow news, negatively related to discount rate news over the past 4 months, and negatively related to the past 10 months of *MES*. These autocorrelation coefficients indicate that contagion and systemic risk make up a reinforcing cycle, which consistent with the model of Adrian and Shin (2014) where banks try to maintain a near constant VaR to equity ratio. As risk aversion and systemic risk decrease, banks become more interconnected due to the lower risk level. However, as banks become more interconnected this increases systemic risk levels 3–12 months in the future which upon realization leads banks to disentangle and decrease the level of financial contagion. This cycle repeats in a self-reinforcing fashion.

6. Financial contagion risk and returns

An important question is whether investors can diversify away the effects of financial contagion. The answer to this question has important implications for policy makers as well as for optimal portfolio allocation. In this and the following section, I argue that financial contagion is not diversifiable and that financial contagion affects the equity risk premium.

6.1. Financial contagion risk and bank returns

Each month, I sort bank stocks into log value-weighted portfolios based on their previous month's average contribution to aggregate financial contagion, $\overline{FC}_t^{(i)} = (T_m)^{-1} \sum_{t=1}^{T_m} FC_t^{(i)}$. T_m denotes the number of trading days in the month. Portfolio returns are observed the following month and then portfolios are re-sorted. The

Table 2
VAR results and cross-autocorrelations. This table presents results from the Campbell and Shiller (1988) cash flow and discount rate VAR decomposition, in Panel A, and cross-autocorrelations with changes in financial contagion, in Panel B. The VAR model used in Panel A is:

$$\mathbf{z}_{t+1} = \mathbf{a} + \mathbf{\Gamma}\mathbf{z}_t + \mathbf{u}_{t+1},$$

where $\mathbf{z}_{t+1} = \left(r_{m,t+1}, r_{f,t+1}, yld_{t+1}\right)'$ is a vector of state variables including the monthly market return, the monthly risk-free rate (1-month rate), and the dividend yield on the S&P 500. $\mathbf{a}$ is a (3 × 1) vector of constant terms, $\mathbf{\Gamma}$ is a (3 × 3) matrix of coefficients, and $\mathbf{u}_{t+1}$ is a (3 × 1) vector of residuals. Innovations in the cash flow factor ($N_{CF,t+1}$) and innovations in the discount rate ($N_{DR,t+1}$) are given by:

$$N_{CF,t+1} = \mathbf{e}_1'(\mathbf{I}_3 + \mathbf{\Lambda})\mathbf{u}_{t+1},$$

$$N_{DR,t+1} = \mathbf{e}_1'\mathbf{\Lambda}\mathbf{u}_{t+1},$$

$$\mathbf{\Lambda} = \rho\mathbf{\Gamma}(\mathbf{I}_3 - \rho\mathbf{\Gamma})^{-1},$$

where $\mathbf{e}_1'$ is the first column from the (3 × 3) identity matrix $\mathbf{I}_3$, $\rho = 1/\left(1 + exp\left[\overline{DP}\right]\right)$, and $\overline{DP}$ is the mean log dividend-price ratio. u_m is the market return residual from the VAR above, *FC* is the estimate of the fraction of bank portfolio return variance attributable to financial contagion obtained from Eq. (2.8), $FC\widehat{\sigma}^2_{r_i}$ is the aggregate level of bank excess covariances, *MES* is the market-value weighted average of marginal expected shortfalls of banks in the bank sample, and *CoVaR* is the market-value weighted average of *CoVaRs* of banks in the bank sample. Results in Panel B are for the exponentially smoothed time series of innovations:

$$MA_t(x) = 0.206299x_t + (1 - 0.206299)MA_{t-1}(x),$$

$$x \in \{u_m, N_{CF}, N_{DR}, \triangle FC, \triangle FC\widehat{\sigma}^2_{r_i}, \triangle MES, \triangle CoVaR\},$$

where the smoothing parameter 0.206299 corresponds to a half-life of approximately 3 months. t-statistics are presented in parentheses, in Panel A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. In Panel B, bold-faced print denotes statistical significance at the 10% level or better. The sample period is January 1960 to December 2011.

Panel A: VAR parameter results

	INT	MRKT	Rf	DIVYLD	N	R^2
MRKT	-0.003	0.079**	-2.353**	0.570***	635	0.020
	(-0.679)	(1.998)	(-2.431)	(2.734)		
Rf	0.000	-0.001	0.949***	0.006*	635	0.933
	(0.429)	(-0.993)	(67.824)	(1.912)		
DIVYLD	0.000**	-0.015***	0.036	0.988***	635	0.992
	(2.163)	(-16.122)	(1.560)	(200.284)		

Panel B: Cross-autocorrelations

Lag	u_m	N_{CF}	N_{DR}	*FC*	$FC\widehat{\sigma}^2_{r_i}$	*MES*	*CoVaR*
$t-12$	−0.049	−0.013	**0.099**	**−0.117**	−0.020	0.017	0.063
$t-11$	0.006	0.042	**0.077**	**−0.135**	−0.009	−0.021	0.045
$t-10$	0.058	**0.081**	0.026	**−0.105**	−0.048	**−0.073**	0.027
$t-9$	**0.111**	**0.127**	−0.009	−0.050	**−0.066**	**−0.104**	0.022
$t-8$	**0.117**	**0.132**	−0.014	0.004	**−0.113**	**−0.124**	0.016
$t-7$	**0.156**	**0.181**	−0.009	−0.013	**−0.120**	**−0.146**	−0.017
$t-6$	**0.189**	**0.213**	−0.026	−0.019	**−0.193**	**−0.152**	−0.012
$t-5$	**0.205**	**0.221**	−0.051	0.001	**−0.149**	**−0.148**	−0.023
$t-4$	**0.208**	**0.210**	**−0.081**	0.022	**−0.142**	**−0.165**	−0.050
$t-3$	**0.183**	**0.165**	**−0.114**	**0.160**	**−0.081**	**−0.170**	**−0.087**
$t-2$	**0.166**	**0.127**	**−0.154**	**0.346**	0.023	**−0.157**	**−0.096**
$t-1$	**0.181**	**0.130**	**−0.185**	**0.636**	0.017	**−0.136**	−0.060
$t+1$	**0.186**	**0.157**	**−0.139**	**0.636**	0.028	−0.016	0.017
$t+2$	**0.158**	**0.146**	**−0.090**	**0.346**	0.012	0.038	0.028
$t+3$	**0.126**	**0.119**	**−0.067**	**0.160**	−0.023	**0.084**	0.025
$t+4$	**0.116**	**0.098**	**−0.088**	0.022	0.010	**0.094**	−0.014
$t+5$	**0.098**	**0.083**	**−0.074**	0.001	0.037	**0.097**	−0.014
$t+6$	0.032	0.017	−0.047	−0.019	**0.093**	**0.131**	0.062
$t+7$	−0.024	−0.033	−0.008	−0.013	**0.163**	**0.117**	**0.092**
$t+8$	−0.045	−0.052	0.004	0.004	**0.176**	**0.137**	**0.099**
$t+9$	−0.047	−0.059	−0.006	−0.050	**0.141**	**0.158**	**0.160**
$t+10$	**−0.087**	**−0.094**	0.019	**−0.105**	**0.169**	**0.167**	**0.082**
$t+11$	**−0.094**	**−0.104**	0.018	**−0.135**	**0.099**	**0.131**	−0.014
$t+12$	**−0.066**	**−0.078**	−0.001	**−0.117**	**0.125**	**0.074**	**−0.078**

full sample of bank returns is trimmed at the 99% level prior to portfolio formation to mitigate the influence of extreme returns.[15]

Table 3 presents return statistics for the contagion sorted bank portfolios. Quintile and tercile sorting methods are presented for robustness. The mean annualized returns for the quintile and the tercile of the most contagious banks are 8.7% and 8.5%, respectively. The mean annualized returns for the least contagious portfolios are 4.2% and 3.6%, respectively. The differences in the mean returns between the most contagious bank portfolios and the least contagious bank portfolios are 4.5% and 4.9% for quintile sorts and tercile sorts, respectively. High-minus-low returns are significantly different from zero at the 5% level or better for each of the sorting methods. This relative outperformance of the high contagion portfolio is indicative that investors holding more contagious banks require higher expected returns.

[15] This sets a bank's monthly return in excess of 39.1% to be 0.

Table 3
Bank contagion portfolio returns. This table presents the mean returns and stock characteristics for the contagion sorted bank portfolios. Each month, banks are sorted into portfolios based on their contribution to the total financial contagion estimate, $FC_t^{(i)}$. In the following month returns on the portfolio are observed and banks are re-sorted. MEAN denotes the time series mean of portfolio returns, T-STAT tests if MEAN is statistically different from zero, SHARPE presents the Sharpe ratio of the portfolio, MVE is mean bank market value of equity (in billions of dollars) in the portfolio, RETSQ is the mean squared return ($\times 10^3$), DVOL is the natural logarithm of the mean dollar volume traded, PI is the mean (Amihud, 2002) price impact illiquidity measure ($\times 10^6$), LAGRET is the annualized mean lagged one-month stock return, MES is the Acharya et al. (2010) bank market-cap weighted marginal expected shortfall measure ($w_{i,t}MES_{i,t} \times 10^3$), and CoVaR is the annualized bank market-cap weighted (Adrian and Brunnermeier, 2016) co-value-at-risk measure ($w_{i,t}CoVaR_{i,t} \times 10^3$). Q5 is the quintile of most contagious banks, Q1 is the quintile of least contagious banks, T3 is the tercile of most contagious banks, and T1 is the tercile of least contagious banks. Stock returns are trimmed at the 99% level prior to portfolio formation. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 1968 to December 2011.

	MEAN	T-STAT	SHARPE	MVE	RETSQ	DVOL	PI	LAGRET	MES	CoVaR
Q5	0.087***	2.777	0.162	4.822	0.716	17.298	0.194	0.098	0.277	0.610
Q1	0.042*	1.875	−0.079	0.256	1.347	14.874	12.508	−0.005	0.021	0.052
T3	0.085***	2.859	0.162	3.118	0.785	16.890	0.639	0.092	0.190	0.422
T1	0.036*	1.692	−0.126	0.172	1.431	14.469	13.626	−0.002	0.015	0.040
Q5-Q1	0.045**	2.264	0.342	.	.	.	.	.	.	.
T3-T1	0.049***	2.766	0.417	.	.	.	.	.	.	.

Table 4
Bank contagion portfolio abnormal returns. This table presents regression results from regressing financial contagion sorted bank portfolios on the FFCPS 5 factors. The regression equation is:

$$r^e_{p,t} = \alpha_p + \beta_{p,MRKT} r^e_{MRKT,t} + \beta_{p,SMB} r_{SMB,t} + \beta_{p,HML} r_{HML,t} + \beta_{p,MOM} r_{MOM,t} + \beta_{p,LIQ} r_{LIQ,t} + \varepsilon_{p,t},$$

where ALPHA is the annualized regression intercept, MRKT denotes the excess market return, SMB is the return on the small-minus-big portfolio, HML is the return on the high B/M-minus-low B/M portfolio, MOM is the return on the winners-minus-losers portfolio, and LIQ is the return on high liquidity exposure-minus-low liquidity exposure portfolio. t-statistics using (Newey and West, 1987) autocorrelation consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 1968 to December 2011.

	ALPHA	MRKT	SMB	HML	MOM	LIQ
T3	−0.046***	1.066***	0.268***	0.585***	−0.024	−0.111***
	(−4.698)	(42.459)	(11.383)	(8.066)	(−0.88)	(−6.113)
T1	−0.071***	0.575***	0.432***	0.438***	−0.027	−0.052**
	(−4.35)	(14.718)	(5.926)	(9.178)	(−1.323)	(−2.386)
T3-T1	0.024***	0.491***	−0.163**	0.147***	0.003	−0.059**
	(2.626)	(25.007)	(−2.04)	(4.115)	(0.253)	(−2.135)

Fig. 4 plots the cumulative return process of a trading strategy, re-balancing monthly, that buys the highest contagion tercile and sells the lowest contagion tercile, denoted as the HCMLC portfolio, in the top panel. The cumulative return from January 1968 to December 2011 for the HCMLC portfolio is 208%. The bottom panel presents monthly returns on the HCMLC portfolio. Consistent with ex-ante expectations, the HCMLC portfolio experiences large losses during the financial crisis as the most contagious banks are hurt by a disproportionately greater amount than the least contagious banks.

HCMLC portfolio Sharpe ratios, in Table 3, are slightly lower than the market Sharpe ratio of 0.560 (not reported) over the same period. The remaining columns present the mean bank stock characteristics in the portfolios. The mean market values of equity (MVE) of the financial stocks included in each portfolio indicate that banks in the most contagious portfolios are larger than those in the least contagious ones. This is not a purely mechanical relationship, however. $FC_t^{(i)}$ is a function of $z_{i,t|t}$ which can take on positive or negative values. The high contagion bank portfolios, relative to the low contagion bank portfolios, also contain banks that have lower realized variances (RETSQ), higher mean log dollar volumes traded (DVOL), lower mean (Amihud, 2002) price impact illiquidities (PI), and higher lagged one-month returns (LAGRET). These portfolio characteristics are consistent with the findings of Adrian and Shin (2014) that financial intermediaries tend to maintain relatively stable probabilities of default. Therefore, the banks that have lower stock variances, lower illiquidity, and higher momentum are able to increase their contagion exposure. The final two columns present the mean *MES*s and *CoVaR*s of the banks held in the portfolios. These are also higher for banks in the most contagious portfolios (as would be expected).

Table 4 presents regression results from regressing financial contagion sorted bank portfolio excess returns on the Carhart (1997) 4-factor model, augmented with the Pástor and Stambaugh (2003) tradable liquidity factor (hereafter, referred to as the FFCPS model). Interestingly, both the most contagious and the least contagious terciles of bank stocks obtain negative alphas, indicating that these groups of stocks are overvalued on average. Gandhi and Lustig (2015) also find that large banks are relatively overpriced, attaining negative alphas, and provides evidence that the relative overpricing of banks is due to government guarantees for these large banks in disaster states.[16] In the same spirit, Kelly et al. (2012) look at the relative pricing of individual bank put options and the financial index sector put option and find evidence that an implicit government put option is priced into the stocks of large banks. The final row presents the long-short contagion portfolio return alphas. The long-short alpha is 2.4% and it is significant at the 1% level. These results provide evidence that investors demand a higher risk premium on the most contagious banks (relative to other banks) and that investors view the least contagious banks as providing a form of insurance against the most contagious ones.

Table 5 presents the mean bank portfolio returns for each decile sorted on financial contagion risk, in Panel A, and tests for a relationship between portfolio expected returns and contagion level, in Panel B. If financial contagion risk enters the SDF, then a positive cross-sectional relationship should be observed between the contagion risk deciles and the decile mean returns. This is because as more contagious banks receive a shock, the shock is passed through to the real economy causing marginal utility and conta-

[16] This implicit government put option need not be of uniform proportional value to bank size. For example, a very large bank may be viewed as too large to bail out resulting in a smaller proportional implicit government put option value being attached to it as compared to a smaller bank. See (Cubillas et al., 2017) for evidence on too-big-to-fail versus too-big-to-save.

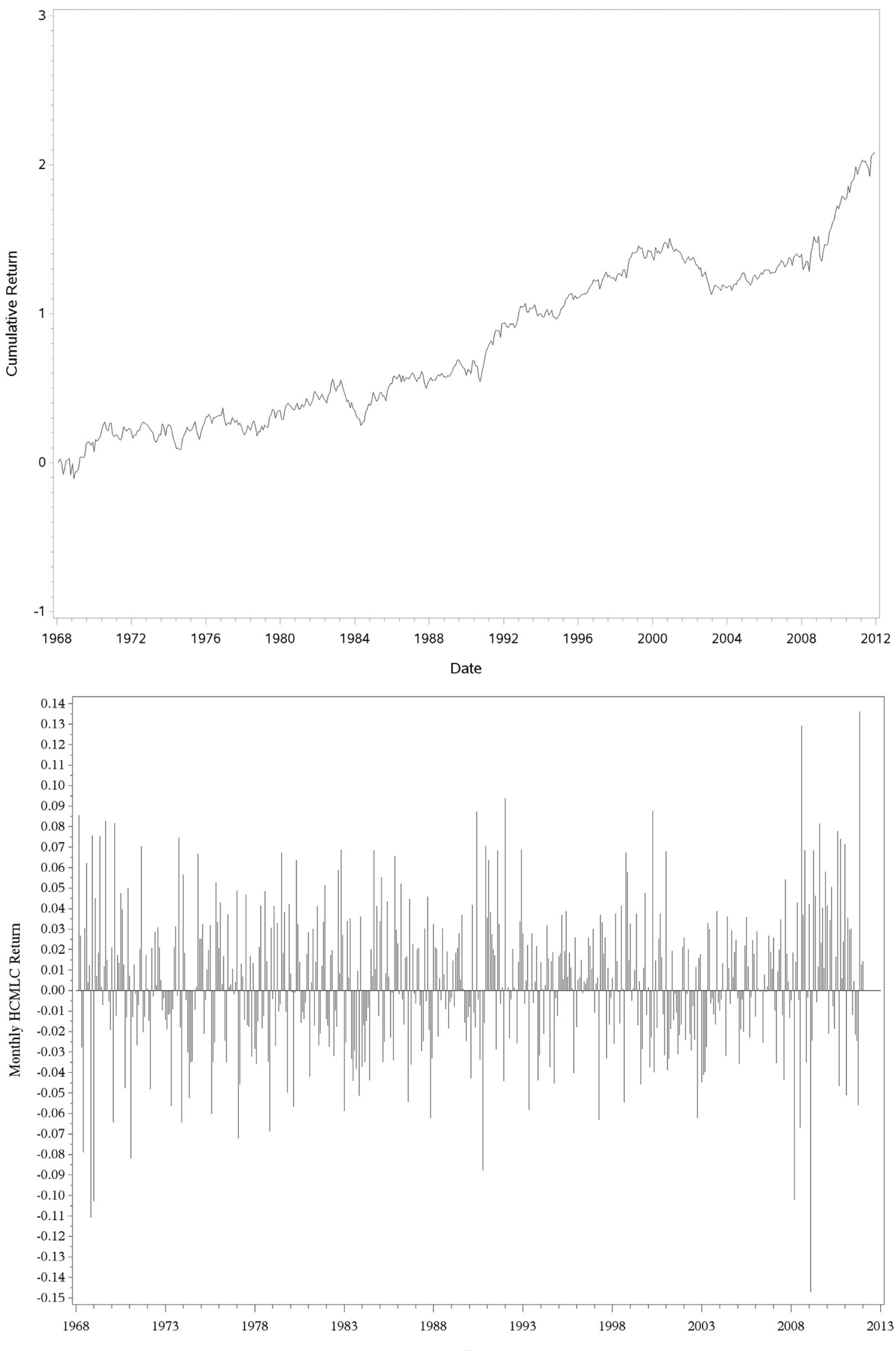

Fig. 4. HCMLC portfolio returns. This figure plots the cumulative return processes for the HCMLC portfolio (the portfolio buys the tercile of most contagious banks and sells the tercile of least contagious banks), with monthly re-balancing, in the top panel. In the bottom panel, the monthly returns on the HCMLC portfolio are presented.

gious bank returns to have a negative covariance. Mean portfolio returns generally increase from the least contagious decile to the most contagious decile. Due to random sampling error, a purely monotonic relationship is unlikely to be observed in practice. Panel B tests for a positive cross-sectional relationship between the portfolio mean returns and the portfolio contagion levels. Two tests, one parametric and one non-parametric, are used to test if the null hypothesis that there is no relationship between bank portfolio contagion risk and portfolio mean return can be rejected. The parametric test regresses mean portfolio returns on a constant and

Table 5
Bank contagion risk and portfolio returns. This table presents mean returns and alphas of the contagion sorted bank portfolios in Panel A and trend tests in Panel B. Each month, banks are sorted into equal-weighted and log value-weighted portfolios based on their contribution to the total financial contagion estimate, $FC_t^{(i)}$. In the following month returns on the portfolio are observed and banks are re-sorted. Contagion sorted decile returns are regressed on the FFCPS 5 factors:

$$r^e_{p,t} = \alpha_p + \beta_{p,MRKT} r^e_{MRKT,t} + \beta_{p,SMB} r_{SMB,t} + \beta_{p,HML} r_{HML,t} + \beta_{p,MOM} r_{MOM,t} + \beta_{p,LIQ} r_{LIQ,t} + \varepsilon_{p,t}.$$

ALPHA is the annualized regression intercept, MRKT denotes the excess market return, SMB is the return on the small-minus-big portfolio, HML is the return on the high B/M-minus-low B/M portfolio, MOM is the return on the winners-minus-losers portfolio, and LIQ is the return on high liquidity exposure-minus-low liquidity exposure portfolio. Decile 10 is the decile of most contagious banks and decile 1 is the decile of least contagious banks. The regression trend test in Panel B regresses decile portfolio returns on a constant and a trend variable ranging from 1 to 10. INT denotes the regression intercept and TREND is the coefficient on the trend variable. Kendall's tau, TAU, is obtained from the methodology described in Kendall (1938). In Panel A, t-statistics are presented in parentheses. In Panel B, t-statistics are presented in parentheses in columns 2 and 3. Kendall's p-values from Kendall (1975) are presented in parentheses in column 4. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 1968 to December 2012.

Panel A: Portfolio returns										
	Contagion decile									
	1	2	3	4	5	6	7	8	9	10
$\mathbf{E}(r_p)$	0.055**	0.026	0.025	0.049**	0.049**	0.051*	0.079***	0.079***	0.081***	0.092***
	(2.241)	(1.183)	(1.119)	(2.135)	(1.974)	(1.887)	(2.682)	(2.64)	(2.638)	(2.736)
Panel B: Expected return trend tests										
	INT	TREND	TAU							
$\mathbf{E}(r_p)$	0.023**	0.007***	0.511**							
	(2.536)	(4.557)	(0.046)							

a cross-sectional trend variable ranging from one to ten. This regression test has the convenient property of providing evidence as to how much additional expected return investors require to hold an adjacently more contagious portfolio of bank stocks. Kendall's tau, a measure of rank correlation, is the non-parametric test.[17] Kendall's tau is a measure of similarity in decile ranking and mean return ranking. If the two rankings are sufficiently similar, then the null hypothesis of no positive relationship between portfolio financial contagion risk and portfolio mean returns is rejected.

Cross-sectional test results, using the regression test, are presented in the first two columns of Panel B and results using Kendall's tau are presented in the final column. The regression test rejects the null hypothesis of no relationship between mean bank portfolio return and portfolio contagion risk at the one% level. The cross-sectional trend coefficient in the regression test indicates that investors require an additional 70 basis points of expected return to hold an adjacently more contagious portfolio of bank stocks. Kendall's tau test rejects the null of no relationship between portfolio contagion risk and expected return as well.

6.2. Financial contagion risk and stock returns

I estimate stocks' exposures to financial contagion risk with the following regression:

$$\begin{aligned} r^e_{i,t} = \beta_{i,0} &+ \beta_{i,MRKT} r^e_{MRKT,t} + \beta_{i,SMB} r_{SMB,t} + \beta_{i,HML} r_{HML,t} \\ &+ \beta_{i,MOM} r_{MOM,t} + \beta_{i,LIQ} r_{LIQ,t} + \beta_{i,HCMLC} r_{HCMLC,t} + \varepsilon_{i,t}. \end{aligned} \tag{6.1}$$

$r^e_{i,t}$ is the excess return on stock i, $r^e_{MRKT,t}$ is the excess return on the market portfolio (MRKT), $r_{SMB,t}$ is the return on the small-minus-big portfolio (SMB), $r_{HML,t}$ is the return on the high B/M-minus-low B/M portfolio (HML), $r_{MOM,t}$ is the return on the winners-minus-losers momentum portfolio (MOM), $r_{LIQ,t}$ is the return on the portfolio of stocks with highest liquidity beta minus the portfolio of stocks with lowest liquidity beta (LIQ), and $r_{HCMLC,t}$ is the return on the tercile of most contagious bank stocks minus the return on the tercile of least contagious bank stocks, denoted the HCMLC portfolio.[18] Eq. (6.1) is estimated in a rolling regression framework, using 60-months of return observations. Stocks are sorted into value-weighted deciles based on their month t HCMLC beta and then portfolio returns are observed in month $t+1$. Eq. (6.1) states that stocks that covary more positively with contagious banks have higher expected returns when high contagion banks outperform low contagion banks and have lower expected returns when contagious banks underperform low contagion banks (relative to their mean expected return determined by the intercept). The intuition for this is that shocks to contagious banks are passed through to these companies with high HCMLC betas (see Section 3) causing investors' marginal utility to covary more negatively with the performance of contagious banks.

Table 6 presents the correlation matrix of factor portfolio returns. Correlations between returns on the HCMLC portfolio, returns on the Chicago Board Options Exchange Market Volatility Index (Δvix), and changes in aggregate corporate default risk (DEF, defined as the log change in the log difference between yields on Baa and Aaa rated bonds) are included to test if the HCMLC portfolio simply captures changing aggregate volatility risk or changing aggregate default risk. HCMLC correlations with the broker-dealer leverage factor (LEV) are included to test for if the HCMLC factor reflects a leverage effect. HCMLC returns are most correlated with the MRKT portfolio at 0.586, in agreement with the link between contagion and systematic risk in Section 5, and have the most negative correlation with Δvix at -0.443. The negative correlation coefficient between HCMLC and Δvix shows that the most contagious banks do relatively worse in more volatile times when they need to disentangle their interconnectedness (see Section 5). The positive correlation between HCMLC returns and DEF of 0.200 can be explained by the spread in implicit government put option values for the most contagious banks and the least contagious banks being greater when *DEF* is higher which leads to the most contagious banks being more overvalued relative to the least contagious banks. HCMLC correlations with the remaining factors, including LEV, are close to 0 indicating that financial contagion risk is a distinct separate risk.

Table 7 presents returns from HCMLC beta sorted stock portfolios where a 60-month rolling window is used to estimate factor betas using Eq. (6.1) and portfolios are re-balanced monthly.[19] The lowest HCMLC beta decile has an annualized mean return of 3.5% and the highest HCMLC beta decile earns a mean return of

[17] The interested reader is referred to Kendall (1938) for details on the test computation.

[18] Asset pricing results are qualitatively unchanged if the HCMLC portfolio is alternatively formed using decile or quintile sorts.

[19] Robustness tests for a wide range of factor loading estimation window sizes are provided in Section D of the Internet Appendix.

Table 6
Factor correlations. This table presents the correlation matrix of monthly factor portfolio returns. HCMLC is the log value-weighted high contagion-minus-low contagion bank portfolio return, MRKT denotes the excess market return, SMB is the return on the small-minus-big portfolio, HML is the return on the high B/M-minus-low B/M portfolio, MOM is the return on the winners-minus-losers portfolio, LIQ is the return on high liquidity exposure-minus-low liquidity exposure portfolio, DEF is the monthly log change in the log difference between yields on Baa and Aaa rated bonds, Δvix is the monthly log return of the Chicago Board Options Exchange Volatility Index, and LEV is the broker-dealer leverage factor of Adrian et al. (2014). The sample period covers January 1968 to December 2011 for correlations excluding Δvix. The sample period for correlations including Δvix is January 1990 to December 2011. The sample period is Q1 1968 to Q4 2009 for correlations including LEV.

	MRKT	SMB	HML	MOM	LIQ	DEF	Δvix	LEV	HCMLC
MRKT	1.000								
SMB	0.307	1.000							
HML	−0.321	−0.241	1.000						
MOM	−0.131	−0.026	−0.149	1.000					
LIQ	−0.052	−0.039	0.031	−0.023	1.000				
DEF	0.022	−0.059	−0.003	−0.042	−0.002	1.000			
Δvix	−0.652	−0.186	0.143	0.147	−0.043	0.090	1.000		
HCMLC	0.586	0.025	−0.052	−0.098	−0.086	0.200	−0.443	0.083	1.000

Table 7
Betas and expected returns. This table presents mean returns and stock characteristics in the log value-weighted stock deciles sorted on financial contagion beta in Panel A. Deciles are sorted based on financial contagion beta in month t from the following regressions:

$$r^e_{i,t} = \beta_{i,0} + \beta_{i,MRKT} r^e_{MRKT,t} + \beta_{i,SMB} r_{SMB,t} + \beta_{i,HML} r_{HML,t} + \beta_{i,MOM} r_{MOM,t} + \beta_{i,LIQ} r_{LIQ,t} + \beta_{i,HCMLC} r_{HCMLC,t} + \varepsilon_{i,t},$$

where MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion bank portfolio return factor. $\overline{\beta}_{MRKT}$, $\overline{\beta}_{SMB}$, $\overline{\beta}_{HML}$, $\overline{\beta}_{MOM}$, and $\overline{\beta}_{LIQ}$ are the mean monthly VW factor loadings from the first step individual firm factor model regressions. FFCPS α is the mean VW stock alpha from the FFCPS factor model (without the *HCMLC* factor included), RETSQ is the mean monthly VW squared return ($\times$ 10), DVOL is the mean natural logarithm of the VW monthly dollar volume traded, PI is the mean monthly (Amihud, 2002) VW price impact illiquidity measure ($\times 10^4$), LAGRET is the annualized mean VW lagged one-month stock return, IV is the mean VW stock return residual standard deviation ($\times$ 10) from estimating the full factor model with the contagion factor, and SKW is the mean VW stock return skewness ($\kappa_i = [3(\mathbf{E}(r_i) - \mathbf{MED}(r_i))]/\mathbf{SD}(r_i)$). The regression trend test in panel B regresses decile portfolio FFCPS alphas on a constant and a trend variable ranging from 1 to 10. INT denotes the regression intercept and TREND is the coefficient on the trend variable. Kendall's tau, TAU, is obtained from the methodology described in Kendall (1938). Stock returns are trimmed at the 99.5% level. t-statistics are presented in parentheses in Panel A. In Panel B, t-statistics are presented in parentheses in rows 2 and 4. Kendall's p-values from Kendall (1975) are presented in row 6. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 1968 to December 2011.

Panel A: HCMLC beta sorted portfolio returns

	Portfolio decile										
	1	2	3	4	5	6	7	8	9	10	10-1
$\overline{\beta}_{HCMLC}$	−1.544	−0.851	−0.549	−0.33	−0.146	0.025	0.202	0.403	0.670	1.256	2.800
FFCPS α	−0.039	−0.008	0.004	0.010	0.014	0.015	0.018	0.020	0.021	0.020	0.060
$\mathbf{E}(r_p)$	0.035***	0.066***	0.076***	0.076***	0.078***	0.079***	0.080***	0.080***	0.075***	0.060***	0.025***
t-stat	(10.911)	(17.416)	(18.86)	(19.118)	(19.402)	(19.600)	(19.625)	(19.528)	(18.928)	(16.267)	(14.507)
$\overline{\beta}_{MRKT}$	1.666	1.313	1.150	1.037	0.947	0.873	0.799	0.731	0.633	0.418	−1.248
$\overline{\beta}_{SMB}$	0.835	0.758	0.705	0.659	0.623	0.627	0.642	0.680	0.758	0.959	0.125
$\overline{\beta}_{HML}$	0.317	0.261	0.243	0.223	0.216	0.212	0.206	0.200	0.184	0.144	−0.173
$\overline{\beta}_{MOM}$	−0.160	−0.121	−0.106	−0.091	−0.084	−0.080	−0.076	−0.072	−0.072	−0.063	0.097
$\overline{\beta}_{LIQ}$	−0.028	0.002	0.001	0.003	0.004	−0.006	−0.004	−0.009	−0.019	−0.045	−0.017
DVOL	20.118	20.919	21.265	21.565	21.768	21.748	21.739	21.670	21.414	21.084	20.605
PI	2.280	1.100	0.748	0.676	0.557	0.528	0.485	0.387	0.357	0.437	−1.843
RETSQ	0.484	0.303	0.237	0.205	0.185	0.207	0.182	0.184	0.202	0.285	−0.199
LAGRET	0.017	0.014	0.013	0.013	0.012	0.012	0.013	0.014	0.014	0.015	−0.002
IV	1.249	1.055	0.957	0.896	0.859	0.845	0.845	0.862	0.897	1.024	−0.225
SKW	0.374	0.313	0.284	0.263	0.251	0.242	0.237	0.238	0.246	0.274	−0.100

Panel B: HCMLC beta sorted portfolio ALPHA trend tests

	INT	TREND	TAU
FFCPS α	−0.020***	0.005***	0.933***
	(−2.691)	(4.149)	(< 0.001)

6.0%. The difference is statistically significant at the one% level. The remaining rows in Panel A present the mean characteristic values for the stocks that are held in each of the portfolios. The portfolios with increasing HCMLC betas have decreasing market betas and increasing HML betas which suggests that stocks that are more susceptible to the effects of financial contagion have less exposure to the market portfolio and are closer to their default threshold. FFCPS (excluding the HCMLC factor) alphas are increasing from −3.9% for the portfolio with the lowest HCMLC beta to 2.0% for the portfolio with the greatest HCMLC beta. The remaining stock characteristics have no clear pattern across contagion-beta portfolios and display U-shaped or inverse U-shaped patterns.

Panel B presents the results from regressing the mean log value-weighted stock FFCPS alphas in the contagion beta portfolios on a constant and a cross-sectional trend variable extending from one to ten to test the null hypothesis of no relationship between portfolio FFCPS alphas and portfolio HCMLC betas. The null is rejected in favor of portfolios with a greater financial contagion beta having a higher alpha. The regression cross-sectional trend coefficient indicates that investors require an additional 50 basis points in expected return per annum, relative to what is predicted by the FFCPS model, to hold an adjacent portfolio with a greater HCMLC beta.

Fig. 5 plots the cumulative return processes from investing in the long-short decile portfolios sorted on betas obtained from Eq. (6.1). Portfolios are formed by buying the decile with the greatest factor beta and selling the decile with the lowest factor beta. Portfolios are rebalanced monthly. Five years of observations are lost in acquiring the first beta estimates. The cumulative return from January 1973 to October 2011 for the HCMLC beta sorted

Fig. 5. Beta-sorted portfolio cumulative return processes. This figure plots the cumulative return processes of portfolios that buy the decile of stocks with greatest factor beta and sell the decile of stocks with lowest factor beta. Portfolios are rebalanced monthly. Factor betas are estimated from the following rolling regression:

$$r_{i,t}^{e} = \beta_{i,0} + \beta_{i,MRKT} r_{MRKT,t}^{e} + \beta_{i,SMB} r_{SMB,t} + \beta_{i,HML} r_{HML,t} + \beta_{i,MOM} r_{MOM,t} + \beta_{i,LIQ} r_{LIQ,t} + \beta_{i,HCMLC} r_{HCMLC,t} + \varepsilon_{i,t}.$$

Rolling 60-month regressions are estimated. The previous 60 months of returns are used to estimate betas, portfolios are rebalanced, and portfolio returns are observed in the following month. The HCMLC beta sorted long-short portfolio cumulative return process is plotted in the top panel. The bottom panel plots beta sorted cumulative return process on commonly used factor portfolios. MRKT (solid line) is the excess market return factor, SMB (dashed line) is the small-minus-big return factor, HML (dash dot line) is the high-minus-low return factor, MOM (dash double dot line) is the momentum return factor, and LIQ (dot line) is the liquidity return factor.

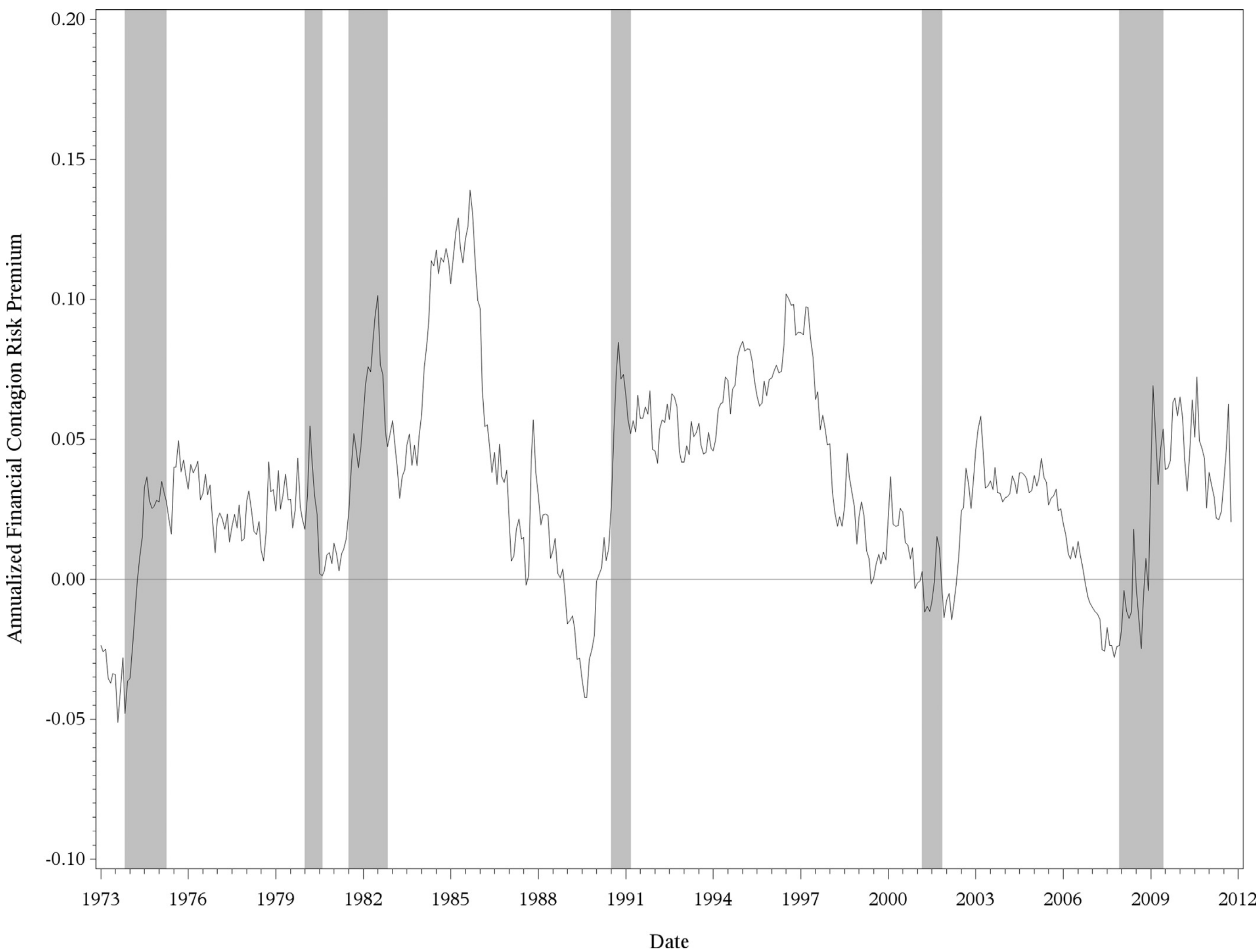

Fig. 6. Time series of financial contagion risk premium. This figure plots the smoothed time series of the estimated financial contagion risk premium, $\widehat{\lambda}_{HCMLC}$, obtained from firm-level Fama–MacBeth regressions as in Table 8. The shaded regions are NBER recession dates. The smoothing procedure used is given by:

$\widehat{\widehat{\lambda}}_{HCMLC,t} = \sum_{m=-h}^{h}\left[\frac{h+1-|m|}{(h+1)^2}\right]\widehat{\lambda}_{HCMLC,t+m}$,

where $h = 23$ (5% of the sample size).

long-short portfolio is 68.1%. Cumulative returns for the MRKT, SMB, HML, MOM, and LIQ beta sorted long-short portfolios are 6.0, 17.3, 137.5, 73.8, and −19.2%, respectively.

7. Financial contagion risk and the SDF

Financial contagion risk is proposed to enter a linear SDF, m_t, given by:

$$0 = \mathbf{E}\left(m_{t+1} r^e_{i,t+1}\right), \tag{7.1}$$

$$m_t = 1 - b_1 r^e_{MRKT,t} - b_2 r_{SMB,t} - b_3 r_{HML,t} - b_4 r_{MOM,t} - b_5 r_{LIQ,t} - b_6 r_{HCMLC,t}, \tag{7.2}$$

$$\mathbf{E}\left(r^e_i\right) = b_1 cov\left(r^e_i, r^e_{MRKT}\right) + b_2 cov\left(r^e_i, r_{SMB}\right) + b_3 cov\left(r^e_i, r_{HML}\right) + b_4 cov\left(r^e_i, r_{MOM}\right) + b_5 cov\left(r^e_i, r_{LIQ}\right) + b_6 cov\left(r^e_i, r_{HCMLC}\right), \tag{7.3}$$

$$\mathbf{E}\left(r^e_i\right) = \lambda_{MRKT}\beta_{i,MRKT} + \lambda_{SMB}\beta_{i,SMB} + \lambda_{HML}\beta_{i,HML} + \lambda_{MOM}\beta_{i,MOM} + \lambda_{LIQ}\beta_{i,LIQ} + \lambda_{HCMLC}\beta_{i,HCMLC}. \tag{7.4}$$

r^e_i denotes stock or portfolio i's excess return, $\beta_{i,j} = \mathbf{CV}\left(r^e_i, r_{j,t}\right)/\mathbf{V}\left(r_{j,t}\right)$, and λ_j is the price of risk associated with the j' th factor. Eq. (7.1) is the no-arbitrage condition stating that risk-adjusted stock returns have a price of zero and Eq. (7.2) specifies the linear form of the SDF. The beta pricing models in Eq. (7.3) and (7.4) are immediately implied. Eq. (7.4) is estimated with the Fama and MacBeth (1973) two-stage regressions at the firm level. 60-month rolling regressions are used in the first stage and the intercept term is excluded in the second stage regression. An intercept term is excluded in the second stage to avoid the restriction of a common underpricing or overpricing in the cross-section of returns that would result. Fama–MacBeth regressions are run with the HCMLC portfolio as the only factor, augmenting the CAPM with HCMLC, augmenting the FF3F model with HCMLC, and augmenting the FFCPS model with HCMLC.

Table 8 presents risk premium results from the firm-level Fama-MacBeth regressions. The coefficient representing the HCMLC risk premium is stable across factor specifications. When the HCMLC augments the CAPM, an annualized risk premium of 4.2% is obtained. This risk premium is in line with the 4.9% sample mean return observed on the HCMLC portfolio. When the FF3F model and the FFCPS model are augmented with the HCMLC factor,

Table 8
Financial contagion risk premium. This table presents the results of firm-level second-stage (Fama and MacBeth, 1973) regressions. A 60-month window is used for the first-stage beta estimations. Fama–MacBeth second-stage regressions are estimated without the intercept term. The regression equations are:

$$\begin{aligned} r^e_{i,t} &= \beta_{i,0} + \beta_{i,MRKT} r^e_{MRKT,t} + \beta_{i,SMB} r_{SMB,t} + \beta_{i,MOM} r_{MOM,t} + \beta_{i,LIQ} r_{LIQ,t} \\ &\quad + \beta_{i,HCMLC} r_{HCMLC,t} + \varepsilon_{i,t}, \\ r^e_{t+1} &= \lambda_{MRKT} \widehat{\beta}_{MRKT,t} + \lambda_{SMB} \widehat{\beta}_{SMB,t} + \lambda_{HML} \widehat{\beta}_{HML,t} + \lambda_{MOM} \widehat{\beta}_{MOM,t} \\ &\quad + \lambda_{LIQ} \widehat{\beta}_{LIQ,t} + \lambda_{HCMLC} \widehat{\beta}_{HCMLC,t} + u_t, \\ \overline{\lambda}_k &= \frac{1}{T} \sum_{t=1}^{T} \widehat{\lambda}_{k,t}, \\ \sigma^2\left(\overline{\lambda}_k\right) &= \widehat{h}(0) + 2 \sum_{j=1}^{\lfloor T^{\frac{1}{2}} \rfloor} w_j h(j), \\ w_j &= 1 - \frac{j}{\left(\lfloor T^{\frac{1}{2}} \rfloor + 1\right)}, \\ \widehat{h}(j) &= \frac{1}{T} \sum_{t=1}^{T-j} \left(\widehat{\lambda}_{k,t+j} - \overline{\lambda}_k\right)\left(\widehat{\lambda}_{k,t} - \overline{\lambda}_k\right). \end{aligned}$$

MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion return factor. Annualized risk premium coefficients, $\overline{\lambda}_k$, are presented. t-statistics from Newey and West (1987) autocorrelation consistent standard errors, $\sqrt{\sigma^2\left(\overline{\lambda}_k\right)}$, are presented in parentheses. Stock returns are trimmed at the 99.5% levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period covers 1968 to December 2011.

	HCMLC	CAPM	FF3F	FFCPS
MRKT		0.057***	0.047***	0.047***
		(3.210)	(3.466)	(3.472)
SMB			0.006	0.006
			(0.403)	(0.403)
HML			0.027**	0.027**
			(2.106)	(2.183)
MOM				-0.023
				(-1.358)
LIQ				0.012
				(0.871)
HCMLC	0.066***	0.042***	0.033***	0.033***
	(4.750)	(4.345)	(3.930)	(3.985)

a financial contagion risk premium of 3.3% is obtained. When HCMLC is the only factor, the risk premium is 6.6%. In all factor specifications, financial contagion risk premiums are statistically significant at the 1% level and are greater in magnitude than the SMB, HML, MOM, and LIQ risk premiums. As a robustness check, I estimate bank contagion contributions using the forward Kalman filter ($z_{t|t-1}$), the rolling OLS estimator (z_{OLS}), *MES*, and *CoVaR*. The resulting *HCMLC* prices of risk results are presented in Section E of the Internet Appendix and the prices of risk are relatively unchanged. Further, as shown in Section F of the Internet Appendix, the results in Table 8 cannot have been attained by random chance and are due to banks' specialness, rather than the idiosyncratic volatility puzzle of Ang et al. (2006).

Table 9 presents results of Fama–MacBeth regressions for test portfolios that include the 25 value-weighted size-B/M sorted portfolios, the 49 value-weighted industry portfolios, and the 10 value-weighted momentum portfolios. A rolling window of 60 months is used in the first stage for factor loading estimates.[20] Industry and momentum portfolios are included, in addition to the traditional size and B/M sorted ones, to satisfy "prescription 1" of Lewellen et al. (2010) for improving asset pricing tests since they do not correlate as highly with the SMB and HML returns. When the CAPM is augmented with the HCMLC factor, the annualized HCMLC risk premium is 7.7%. When the FF3F and FFCPS models are augmented with the HCMLC factor, the HCMLC risk premiums are, respectively, 5.0% and 4.5%. These prices of risk are also similar to the annualized mean returns for the HCMLC portfolio.

[20] Robustness tests for a wide range of factor loading estimation window sizes are provided in Section D of the Internet Appendix.

Table 9
Pricing test portfolios. This table presents the results of second-stage (Fama and MacBeth, 1973) regressions. The estimation procedure is the same as presented in Table 8. MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity factor, and HCMLC is the high contagion-minus-low contagion return factor. The test portfolios include the 25 size-B/M portfolios, the 49 industry portfolios, and the 10 momentum portfolios. Portfolio returns are trimmed at the 0.5% and 99.5% levels in the first-stage factor regressions. t-statistics using (Newey and West, 1987) autocorrelation consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period covers January 1968 to December 2011.

	HCMLC	CAPM	FF3F	FFCPS
MRKT		0.072**	0.056**	0.062**
		(2.477)	(1.968)	(2.244)
SMB			0.025	0.025
			(1.256)	(1.356)
HML			0.033*	0.032*
			(1.954)	(1.845)
MOM				0.049**
				(2.152)
LIQ				0.019
				(0.824)
HCMLC	0.070*	0.077***	0.050**	0.045**
	(1.930)	(3.074)	(2.136)	(2.015)

In addition to the dynamic Fama–MacBeth cross-sectional regressions, I also estimate the price of HCMLC risk in full-sample two-pass cross-sectional regressions. Risk premium parameters in Eq. (7.4) are estimated using regular ordinary least squares (OLS) and two alternative specifications of feasible generalized least squares (FGLS). FGLS estimators are included to accommodate the empirical regularity that the residuals from estimating factor models are correlated. The two FGLS specifications differ in the assumed structure of the error covariance matrix, $\boldsymbol{\Omega}_j$ for $j \in \{1, 2\}$. In the first specification, denoted GLS_1, errors are allowed to be heteroskedastic where the error covariance matrix is modeled as:

$$\overline{\boldsymbol{r}}^e = \widehat{\mathbf{B}} \boldsymbol{\Lambda} + \boldsymbol{v}, \tag{7.5a}$$

$$\widehat{\boldsymbol{v}}^2 = \left(\overline{\boldsymbol{r}}^e - \widehat{\mathbf{B}} \widehat{\boldsymbol{\Lambda}}_{OLS}\right) \circ \left(\overline{\boldsymbol{r}}^e - \widehat{\mathbf{B}} \widehat{\boldsymbol{\Lambda}}_{OLS}\right), \tag{7.5b}$$

$$ln\left(\widehat{\boldsymbol{v}}^2\right) = c_0 + \widehat{\mathbf{B}}\mathbf{C} + \boldsymbol{u}, \tag{7.5c}$$

$$\widehat{\widehat{\boldsymbol{v}}}^2 = \exp\left(\widehat{c}_0 + \widehat{\mathbf{B}}\widehat{\mathbf{C}}\right), \tag{7.5d}$$

$$\widehat{\boldsymbol{\Omega}}_1 = diag\left(\widehat{\widehat{\boldsymbol{v}}}^2\right). \tag{7.5e}$$

Hats above variables denote that they have been estimated and $\circ$ denotes the Hadamard element-by-element matrix multiplication operator. Eq. (7.5a) is the standard cross-sectional OLS equation corresponding to Eq. (7.3). $\overline{\boldsymbol{r}}^e$ denotes sample mean portfolio excess return. c_0 and $\mathbf{C}$ are a coefficient and a vector of coefficients to be estimated with Eq. (7.5c). $\widehat{\mathbf{B}}$ is the matrix of estimated betas where row i of $\widehat{\mathbf{B}}$ is the transposed vector of beta coefficients estimated for portfolio i from Eq. (7.1). $\boldsymbol{\Lambda}$ is the vector of factor risk premium coefficients to be estimated in Eq. (7.4). Since $\boldsymbol{\Omega}_1$ is a diagonal matrix in this specification, GLS_1 is also the weighted least squares (WLS) estimator of risk-premiums. The second FGLS specification, denoted GLS_2, uses an error variance matrix that allows

Table 10
Price of risk in the rross-section. This table presents asset pricing test results of the price of financial contagion risk in the cross-section of test portfolio returns. The following two-pass cross-sectional methodology is used:

$$r^e_{i,t} = \beta_{i,0} + \beta_{i,MRKT} r^e_{MRKT,t} + \beta_{i,SMB} r_{SMB,t} + \beta_{i,HML} r_{HML,t} + \beta_{i,MOM} r_{MOM,t} + \beta_{i,LIQ} r_{LIQ,t} + \beta_{i,HCMLC} r_{HCMLC,t} + \varepsilon_{i,t},$$
$$\overline{r}^e_i = \lambda_{MRKT} \widehat{\beta}_{i,MRKT} + \lambda_{SMB} \widehat{\beta}_{i,SMB} + \lambda_{HML} \widehat{\beta}_{i,HML} + \lambda_{MOM} \widehat{\beta}_{i,MOM} + \lambda_{LIQ} \widehat{\beta}_{i,LIQ} + \lambda_{HCMLC} \widehat{\beta}_{i,HCMLC} + u_i,$$

where $\overline{r}^e_i$ is the sample mean excess return of portfolio i and hats denote estimated values. MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion bank portfolio return factor. The test portfolios include the 25 size-B/M portfolios, the 49 industry portfolios, and the 10 momentum portfolios. OLS denotes that estimates were obtained from OLS, GLS_1 uses an error variance matrix that allows for heteroskedastic residuals, and GLS_2 uses an error variance matrix that allows for correlated residuals across portfolios in the first-stage regression. Shanken (1992) standard errors are presented in parentheses. SF denotes the Shanken adjustment factor. Returns are trimmed at the 0.5% and 99.5% levels in the first-stage factor regression. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 1968 to December 2011.

	MRKT	SMB	HML	MOM	LIQ	HCMLC	N	$\overline{R}^2$	SF
OLS	0.066***	0.018	0.024	0.094***	0.086***	0.047***	84	0.244	1.125
	(2.720)	(1.106)	(1.542)	(4.037)	(4.611)	(2.636)			
GLS_1	0.075***	−0.018	0.022	0.100***	0.132***	0.050***	84	0.008	1.194
	(3.069)	(−1.107)	(1.400)	(4.318)	(7.090)	(2.777)			
GLS_2	0.069***	0.042**	0.034**	−0.026	0.110***	0.021	84	0.018	1.115
	(2.810)	(2.504)	(2.103)	(−0.760)	(5.488)	(0.925)			

Table 11
Pricing error tests. This table presents chi-square statistics testing for if all pricing errors are jointly equal to zero. Fama–MacBeth regressions are used in Panel A and two-pass cross-sectional regressions are used in Panel B. The regression specifications are:

$$\begin{aligned} r^e_{i,t} &= \beta_{i,0} + \beta_{i,MRKT} r^e_{MRKT,t} + \beta_{i,SMB} r_{MRKT,t} + \beta_{i,HML} r_{HML,t} + \beta_{i,MOM} r_{MOM,t} \\ &\quad + \beta_{i,LIQ} r_{LIQ,t} + \beta_{i,HCMLC} r_{HCMLC,t} + \varepsilon_{i,t}, \\ \overline{r}^e_i &= \lambda_{MRKT} \widehat{\beta}_{i,MRKT} + \lambda_{SMB} \widehat{\beta}_{i,SMB} + \lambda_{HML} \widehat{\beta}_{i,HML} + \lambda_{MOM} \widehat{\beta}_{i,MOM} + \lambda_{LIQ} \widehat{\beta}_{i,LIQ} \\ &\quad + \lambda_{HCMLC} \widehat{\beta}_{i,HCMLC} + \alpha_i, \end{aligned}$$

where MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion return factor. The pricing error test statistic for the Fama–MacBeth regressions is:

$$\begin{aligned} &\widehat{\boldsymbol{\alpha}}' cov(\widehat{\boldsymbol{\alpha}})^{-1} \widehat{\boldsymbol{\alpha}} \sim \chi^2_{N-k}, \\ &\widehat{\boldsymbol{\alpha}} = T^{-1} \sum_{t=1}^{T} \widehat{\boldsymbol{\alpha}}_t, \\ &cov(\widehat{\boldsymbol{\alpha}}) = T^{-2} \sum_{t=1}^{T} (\widehat{\boldsymbol{\alpha}}_t - \widehat{\boldsymbol{\alpha}})(\widehat{\boldsymbol{\alpha}}_t - \widehat{\boldsymbol{\alpha}})', \end{aligned}$$

and the pricing error test statistic for the cross-sectional regressions is:

$$\begin{aligned} &\widehat{\boldsymbol{\alpha}}' cov(\widehat{\boldsymbol{\alpha}})^{-1} \widehat{\boldsymbol{\alpha}} \sim \chi^2_{N-k}, \\ &\widehat{\boldsymbol{\alpha}} = \overline{\boldsymbol{r}}^e - \widehat{\boldsymbol{\beta}} \widehat{\boldsymbol{\lambda}}, \\ &\boldsymbol{\Sigma}^{(i,j)} = \frac{\boldsymbol{\varepsilon}_i' \boldsymbol{\varepsilon}_j}{T-k}, \\ &\boldsymbol{\Sigma}_f^{(i,j)} = \frac{1}{T} \left(\boldsymbol{f}_i - \overline{f}_i\right)' \left(\boldsymbol{f}_j - \overline{f}_j\right), \\ &cov(\widehat{\boldsymbol{\alpha}}) = \frac{1}{T} \left(\boldsymbol{I}_N - \widehat{\boldsymbol{\beta}} \left(\widehat{\boldsymbol{\beta}}' \widehat{\boldsymbol{\beta}}\right)^{-1} \widehat{\boldsymbol{\beta}}' \right) \boldsymbol{\Sigma} \left(\boldsymbol{I}_N - \widehat{\boldsymbol{\beta}} \left(\widehat{\boldsymbol{\beta}}' \widehat{\boldsymbol{\beta}}\right)^{-1} \widehat{\boldsymbol{\beta}}' \right)' \times \left(1 + \widehat{\boldsymbol{\lambda}}' \boldsymbol{\Sigma}_f \widehat{\boldsymbol{\lambda}}\right). \end{aligned}$$

χ^2_{N-k} estimates are presented. The test portfolios include the 25 size-B/M portfolios, the 49 industry portfolios, and the 10 momentum portfolios. Test portfolio returns are trimmed at the 0.5% and 99.5% levels. ***, **, and * denote statistical significance at the 1%, 5%, 10% levels, respectively. The sample period is January 1968 to December 2011.

	CAPM	FF3F	FFCPS	HCMLC
	Panel A: Fama–MacBeth pricing error statistics			
HCMLC	226.935***	211.300***	192.149***	215.405***
	Panel B: Cross-sectional pricing error statistics			
HCMLC	237.066***	241.116***	242.383***	237.905***

for correlated residuals across portfolios in Eq. (7.1) and is modeled as:

$$\widehat{\boldsymbol{\varepsilon}}_i = \boldsymbol{r}^e_i - \mathbf{F} \widehat{\boldsymbol{\beta}}_i, \tag{7.6a}$$

$$\widehat{\boldsymbol{\Omega}}_2^{(i,j)} = \frac{\widehat{\boldsymbol{\varepsilon}}_i' \widehat{\boldsymbol{\varepsilon}}_j}{(T-k)}, \tag{7.6b}$$

where Eq. (7.6a) is Eq. (7.1) in matrix form and $\widehat{\boldsymbol{\Omega}}_2^{(i,j)}$ denotes the (i, j) element of the $\widehat{\boldsymbol{\Omega}}_2$ matrix.

Table 10 presents the cross-sectional risk premium results. Standard errors for the OLS regression are White (1980) heteroskedasticity consistent standard errors adjusted by the Shanken (1992) correction to account for portfolio betas being estimated in the first step. FGLS standard errors are also adjusted by the Shanken (1992) correction and Shanken correction factors are presented in the final column of the table. The HCMLC factor is significantly priced in the test portfolios using OLS and GLS_1. The risk-premium estimates from the OLS and GLS_1 models are 4.7% and 5.0%, respectively.

Since financial contagion and financial intermediary leverage levels are expected to be related (Allen and Gale, 2000), it may be that the HCMLC factor in the present paper is simply picking up the effects leverage. Section E of the Internet Appendix shows that this is not the case. When asset pricing tests are repeated, additionally including the LEV factor of Adrian et al. (2014), both the HCMLC and LEV factors continue to obtain significant risk premiums. That the HCMLC and LEV factors do not subsume each other provides evidence that neither financial contagion nor bank leverage is a sufficient statistic for the other.

Tests of Fama–MacBeth and cross-sectional pricing errors are provided in Table 11. Panel A tests if the Fama–MacBeth pricing errors are jointly equal to zero for each of the factor model specifications where the chi-square test is used to test if all pricing errors are significantly different from zero. Pricing error results when the HCMLC factor is the only factor are presented in the final column. The null hypothesis that pricing errors are jointly all equal to zero is rejected for all factor models. The HCMLC factor alone, however, prices the test portfolios as well as the CAPM (indicated by the smaller chi-square statistic) and the FF3F model. Panel B presents chi-square statistics, with the Shanken (1992) correction, testing if the pricing errors from the cross-sectional regressions are jointly equal to zero. Cross-sectionally, the HCMLC factor alone prices the test portfolios as well as the CAPM, FF3F, and FFCPS models.

Fig. 6 plots the smoothed time series of financial contagion risk premiums estimated from firm-level Fama-MacBeth regressions. Shaded regions are NBER recession dates. The HCMLC risk premium is counter-cyclical and increases during recessionary periods. The risk premium also tends to be large during the 1990-’98 period, a period where numerous foreign countries were experiencing banking crises. Also of note is the large increase in the risk premium during the 2007-’09 financial crisis period.

Table 12
Sub-period robustness. This table presents the results of second-stage (Fama and MacBeth, 1973) regressions using the firm-level common stock sample. The estimation procedure is the same as presented in Table 8. MRKT is the excess market return factor, SMB is the small-minus-big return factor, HML is the high-minus-low return factor, MOM is the momentum return factor, LIQ is the liquidity return factor, and HCMLC is the high contagion-minus-low contagion return factor. Stock returns are trimmed at the 99.5% level. t-statistics using (Newey and West, 1987) autocorrelation consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	MRKT	SMB	HML	MOM	LIQ	HCMLC
1975-1987	0.087**	0.069**	0.022*	-0.035	0.004	0.053***
	(2.231)	(2.431)	(1.818)	(−1.167)	(0.206)	(3.134)
1987-1999	0.062	-0.010	0.007	0.008	−0.026*	0.043**
	(1.438)	(−0.514)	(0.495)	(0.508)	(−1.689)	(2.237)
1999-2012	0.037	−0.008	0.039	−0.057*	0.051***	0.017*
	(0.786)	(−0.269)	(1.523)	(−1.883)	(2.903)	(1.813)

Sub-period consistency test results for the financial contagion risk premium are presented in Table 12 using the firm-level common stock sample. Risk premium results from firm level second-stage Fama–MacBeth regressions during non-overlapping 12-year periods[21] between 1975 and 2012 are presented. The 5-year period prior to a 12-year window beginning is used to compute the initial betas for the Fama–MacBeth regressions. For example, the cross-sectional test in January 1975 uses betas estimated from January 1970 to December 1974, the cross-sectional regression in February 1975 uses betas estimated from February 1970 to January 1975, and so on. Financial contagion risk premiums are robust to the sub-period examined with HCMLC risk premiums ranging from 1.7% in the 1999–2012 period to 5.3% in the 1975–1987 period.

8. Conclusion

Financial intermediaries provide access to credit and serve as agents investing on households' behalf which makes them uniquely able to affect households' consumption opportunity sets and their marginal utilities. As the propensity for banks to experience shocks simultaneously increases, households' payoffs experience greater covariation with their consumption possibilities. An increase in financial contagion today is significantly associated with higher market returns, higher cash flows, lower discount rates, and lower *MES*, at present, but is associated with lower market returns, lower cash flows, higher *MES*, and higher *CoVaR* 3-12 months in the future. Modern portfolio theory proposes that assets that experience greater covariation in returns with aggregate consumption require a higher expected return. Therefore, investors with short-term time preference require a greater expected return on assets that covary more strongly with contagious banks.

I contribute to the growing financial intermediary asset pricing literature by estimating banks' contributions to aggregate financial contagion in a new state space framework and by showing that financial contagion risk is priced in the cross-section of stock returns. I define the financial contagion risk factor (HCMLC) as the portfolio that buys the tercile of banks that contribute the most to financial contagion and sells the tercile of banks that contribute the least to financial contagion. Banks in the high contagion tercile outperform those in the low contagion tercile by a risk-adjusted 2.4%. The null hypothesis of no relationship between expected returns and financial contagion risk is rejected in favor investors requiring an additional 70 basis points in expected return per annum to hold an adjacent decile of bank stocks that have greater contagion risk. Further, investors require an additional 50 basis points in expected return per annum, relative to what is predicted by the FFCPS model, to hold an adjacent stock decile with a greater HCMLC beta.

Financial contagion risk is priced in the cross-section of firm-level common stock returns as well as in the cross-section of the 25 size-B/M portfolios, the 49 industry portfolios, and the 10 momentum portfolios. The estimated financial contagion risk premium falls within 3.0 % t to 7.3%, depending on factor model specification and test portfolios, which is in line with the sample mean of 4.9% that the HCMLC portfolio obtains. Using the Fama–MacBeth and full sample cross-sectional pricing errors, the HCMLC factor alone prices the 25 size-B/M, 49 industry, and 10 momentum portfolios approximately as well as the FF3F model and the CAPM.

[21] The final sub-period contains 13 years.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jbankfin.2017.01.012

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