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OFFICE MARKET INTERCONNECTEDNESS AND SYSTEMIC RISK EXPOSURE

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Office Market Interconnectedness and Systemic Risk Exposure

Abstract

We empirically examine how systemic risk in the banking sector leads to correlated risk in office markets of global financial centers. In so doing, we compute an aggregated measure of systemic risk in financial centers as the cumulated expected capital shortfall of local financial institutions. Our identification strategy is based on a double counterfactual approach by comparing normal with financial distress periods as well as office with retail markets. We find that office market interconnectedness arises from systemic risk during financial turmoil periods. Office market performance in a financial center is affected by returns of systemically linked financial center office markets only during a systemic banking crisis. In contrast, there is no evidence of correlated risk during normal times and among the within-city counterfactual retail sector. The decline in office market returns during a banking crisis is larger in financial centers compared to non-financial centers.

Keywords: Commercial real estate; correlated risk; financial center; spatial econometrics; systemic risk.

JEL Classification: *G15, R30*

1 Introduction

This paper empirically analyzes how systemic risk in the financial sector leads to the interconnectedness of international commercial real estate markets. Property markets offer a unique testing ground to study whether and how the near collapse of the financial system leads to correlated risk in real asset markets. The undercapitalization of banks triggers a devaluation of financial but also real assets, which are owned and leased by financial institutions in financial centers. We look at this devaluation effect that a burst of an asset bubble in financial markets and a simultaneous increase in systemic risk among financial institutions have on financial center office markets.

Real estate markets are extremely vulnerable to shocks when property prices are inflated and yields are extremely low. As a consequence, risk spillovers in the global banking sector lead to correlated risk in international office property markets in the short-term. We use a spatial econometric model in order to test how the systemic risk channel leads to cross-sectional return dependence in financial center office markets. By focusing on systemic risk reflected in the risk premium, which is unrelated to macroeconomic fundamentals, we control for the credit channel, funding liquidity, and macroeconomic influences as additional components of the property yield in our estimation strategies. These additional medium- or long-term effects on real estate markets are well-documented in the literature (see, e.g., Case, Glaeser, and Parker (2000)).

To test whether systemic risk in the banking sector leads to correlated risk in commercial real estate, we use a large cross-section of international city-level property market returns. The sample includes the dotcom bubble burst in 2000/2001, the global financial crisis 2007/2008, and the European sovereign debt crisis 2010/2011, providing sufficient temporal variation to study the systematic differences in the return dependence among commercial real estate markets between normal and crisis periods. The identification strategy is based on a double counterfactual approach. Imposing time-varying restrictions in our empirical model, we first test for systemic risk as a channel for correlated

risk in financial center office markets during crises relative to non-crisis periods. We then apply a placebo test for cross-sectional dependence among financial center retail markets as within-city counterfactuals during periods of financial distress. While office and retail markets follow a common city-specific trend, their performance should be different during turmoil times, when financial institutions occupying office space are exposed to valuation shocks.

As a proxy for systemic risk, we use the SRISK measure of Brownlees and Engle (2017), which calculates the expected capital shortfall of financial institutions conditional on a hypothetical price decline in the global asset market. Other systemic risk indicators, such as the marginal expected capital shortfall (MES) of Acharya, Pedersen, Philippon, and Richardson (2017) or ΔCoVaR of Adrian and Brunnermeier (2016) are highly correlated with the banks' market beta or Value-at-Risk (VaR). SRISK includes leverage and debt of the banking sector and is therefore more suitable to disentangle systemic from systematic risk (Benoit, Colliard, Hurlin, and Pérignon (2017)). We exploit the hypothetical nature of the SRISK measure to test for common systemic risk in financial centers as a channel for office market interconnectedness. Balance sheets of financial institutions are only affected by a capital shortfall during periods of financial distress. Hence, when market prices fall, systemic banking sector risk should trigger cross-sectional dependence within commercial real estate office markets in financial centers. During normal times, financial institutions are less exposed to valuation shocks and the expected undercapitalization due to a hypothetical stock market decline should not lead to interconnected office markets.

We find empirical evidence of cross-sectional return dependence among financial center office markets during the global financial crisis 2007/2008. This correlated risk can be related to the common systemic risk contribution of financial institutions. As suggested by the hypothetical character of our systemic risk measure, return co-movements among financial center office markets do not exist during normal times. Likewise, no correlated

risk arises in the within-city counterfactual retail sector during crisis periods. Hence, systemic risk of the banking sector does not imply cross-sectional dependence among retail markets. Our main finding holds conditional on a crisis dummy and the stand-alone total expected capital shortfall of the banking sector in a financial center, which indicate no clear statistically or economically significant relationship with the local office market. This result demonstrates the importance of contagion effects among systemically relevant financial institutions for global office property markets compared to the isolated expected capital shortfall of financial institutions within a city.

The results are robust, when we include additional control variables in our model to rule out macroeconomic effects and alternative channels of cross-sectional dependence among commercial real estate markets. Specifically, we control for global GDP growth and credit supply of the banking sector, which are identified as drivers for synchronous return dynamics among international property markets (see, e.g., Case, Goetzmann, and Rouwenhorst (2000), Davis and Zhu (2011)). Potential concerns about both channels can also be mitigated by our double counterfactual approach. If either of these channels is driving our results, we would expect to observe cross-sectional dependence in the counterfactual retail sector during crisis periods or among office markets during normal times. We also disentangle co-movements among office markets that arise from the exposure to systemic banking sector risk from common systematic risk of local banks by additionally controlling for interest rate or credit risk (e.g., see Begenau, Piazzesi, and Schneider (2015)). Correlated risk in financial center office markets also prevails when controlling for a global property market portfolio or conditional on the MSCI world equity index as the main driver for SRISK.

As an additional robustness test, we find no evidence of correlated risk in non-financial center office markets. This is corroborated by our result of a lower average level of total expected capital shortfall in non-financial compared to financial centers. As proxied by the SRISK contribution of financial institutions with local main offices,

the relative size of the banking sector in non-financial centers is systemically irrelevant for the local office market. Furthermore, we rule out that the correlated risk among international financial center office markets picks up other crisis effects than the systemic risk during the global banking crisis. For instance, we find no evidence of office market interconnectedness during the European sovereign debt crisis in 2010/2011 or the dotcom bubble burst in 2000/2001. The sovereign debt crisis was confined to few European countries and bailout strategies for local banks prevented contagious spillovers to the global financial system (Lane (2012)). In contrast, the dotcom bubble was related to the overvaluation of technology companies (e.g., Ofek and Richardson (2003), Griffin, Harris, Shu, and Topaloglu (2011)). Its burst in 2000 potentially led to a lower demand of stock exchange services, but not implied correlated risk.

Our spatial model shows the immediate effect of the valuation shock leading to correlated risk because of the interconnectedness of financial center office markets. To quantify the impact of systemic risk on the office market return performance, we apply a difference-in-difference model. Accompanied by the correlated risk during the crisis period, we show a statistically significant decline in office market returns in comparison to the within-city counterfactual retail sector. Similarly, office market returns are lower in financial than in non-financial centers during the aftermath of the financial crisis 2007/2008. An asset price bubble burst results in an average annual decrease in office relative to retail market returns of 11%-points during the financial crisis 2008/2009. Moreover, office market returns in financial centers decrease by 12%-points compared to non-financial centers during the global financial crisis period.

This paper contributes to the empirical discussion on the interconnectedness of asset markets during periods of financial distress. Bekaert, Harvey, and Ng (2005) and Bekaert, Ehrmann, Fratzscher, and Mehl (2014) analyze excess return co-movements among global equity markets during financial turmoil periods, which cannot be explained by common risk factors. Cotter, Gabriell, and Roll (2015) and Landier, Sraer, and Thesmar (2017) link

co-movements in the residential housing market to macroeconomic conditions, mortgage securitization, and funding liquidity from an integrated banking sector. The literature is mostly silent on co-movements among commercial real estate markets. Exceptions are Case, Goetzmann, and Rouwenhorst (2000), who relate property market co-movements to a global GDP pattern or Stevenson, Akimov, Hutson, and Krystalogianni (2014), who find evidence of synchronized office market cycles.

We also build on the literature of systemic risk which is based on the correlation of the market price of assets in the balance sheet of financial institutions (e.g., Acharya, Engle, and Richardson (2012), Acharya, Pedersen, Philippon, and Richardson (2017), Brownlees and Engle (2017)). Allen, Babus, and Carletti (2012) and Adrian and Brunnermeier (2016) show how a shock in one institution affects the entire financial system. In contrast, we study synchronous price declines and correlated risk in commercial real estate, which provide the potential for reinforced valuation shocks, undercapitalized banks, and thus, global systemic risk (see, e.g., Antoniadou (2019)). Our results are consistent with Brunnermeier, Rother, and Schnabel (2019) who illustrate how systemic risk and the resulting banking crisis lead to a devaluation of overvalued assets and spillovers to the rest of the economy.

Our findings help for a better understanding of the fragility of commercial property markets in financial centers, particularly at times when financial institutions are vulnerable to valuation shocks. Knowledge about how commercial real estate markets are exposed to systemic risk is essential for policy makers and regulatory authorities. Systemic risk as a transmission channel for correlated risk in commercial real estate markets and co-movements with other financial assets, such as stocks, has also important risk management implications for investors. For instance, our findings imply that risk diversification strategies among international financial center office markets and across asset classes lose their effectiveness in crisis times when financial protection is most needed.

The remainder of the paper is structured as follows. Section 2 provides the concep-

tional framework. Section 3 describes the data. Section 4 introduces the methodology and discusses the identification strategy. Section 5 presents the empirical results. Section 6 concludes.

2 Global Financial Crisis, Systemic Risk, and International Office Markets

The global financial crisis in 2007/08 and the systemic risk in the banking sector had their origin in the bubble burst at the U.S. housing market and the triggered subprime mortgage crisis. Banks suffered substantial residential mortgage losses, which led to a credit crunch and the deterioration of capital positions. At that point in time, commercial real estate markets were still at their peak, i.e., property prices were high and yields were extremely low (e.g., Levitin and Wachter (2013)). The increasing risk in the banking sector caused the interbank funding to dry-up and, as banks were highly connected through counterparty risk, contagion effects crossed the international banking sector (Brunnermeier (2009)). Stricter financial conditions and the devaluation of collateral led to further price depreciation. This negative feedback loop was enforced by the stock market performance, which affected the net worth of financial institutions due to the marked-to-market valuation of their assets and again reinforced systemic risk.

How soaring systemic risk affected yields of commercial real estate, particularly office markets in financial centers, can be illustrated by the simple framework of Duca and Ling (2018):

$$cap = \frac{\overline{NCF}}{V} = r_F + rp - g - liq^{funding}, \quad (1)$$

where the expected yield, represented by the capitalization rate and defined as ratio of generated net rent cash flow ($\overline{NCF}$) from commercial real estate relative to the market value (V), can be explained by the risk-free rate (r_F), the required risk premium (rp),

long-term rental growth expectations (g), and funding liquidity ($liq^{funding}$).

Because office space in financial centers is used by property-owners and tenants from the financial service industry, rental values and property returns are linked to financial market price fluctuations (see, e.g., Lizieri, Baum, and Scott (2000), Lizieri and Pain (2014)). Office property market values $V = \frac{\overline{NCF}}{cap}$ devaluated at still contractually fixed net cash flows ($\overline{NCF}$) because of capital shortage triggered by fire-sales and asset price declines. This massive devaluation of office properties is expected to be stronger in local markets accommodating more systemically relevant banks, because financial institutions have to readjust their real estate assets on their balance sheets.

Similar to Ghysels, Plazzi, and Valkanov (2007), the effect of systemic risk can be interpreted as the orthogonal part in the cap rate predictability, which is unrelated to (long-term) economic conditions and growth in future rents (g). This short-term devaluation is driven by the systemic risk or the expected shortfall of the banking sector and can be channeled through a higher risk premium of Equation (1). The negative expectation of investors and declining credit ratings of financial institutions lead to an increase in the risk premium (rp). Due to this increase in the risk premium and because financial institutions operate in global financial centers, we conjecture that their high interconnectedness, and particularly, the resulting simultaneous decrease in commercial real estate prices leads to co-movements of international office markets. We interpret this correlated risk in terms of spillover effects.

In our estimation strategy, we model these co-movements and spillover effects in terms of correlated risk by spatial econometrics. For our identification strategy, we derive two testable restrictions: First, because of the direct exposure of systemically relevant banks to overvalued assets, we expect correlated risk to occur only in financial center office markets. Second, as this valuation shock on commercial real estate is triggered by the systemic risk channel, these co-movements should only be observed during the global financial crisis period 2007/2008.

We also control for additional channels: In the financial crisis, and prior to the great recession, investors in the office property market expected lower future cash flows (g) due to credit losses and declining profitability of the banking sector. The market for commercial real estate had seen a decline in realized rental cash flow when the global economy ran into the great recession, which led to job cuts in the financial sector, with lower demand for office space and increased vacancy rates. At the same time, tightening credit supply and lending standards dried-up the funding liquidity ($liq^{funding}$). Together with a higher interest rate (r_F) as the original trigger of the subprime crisis, all these effects drove up the expected cap rate.

3 Data

In Sub-Section 3.1, we discuss our commercial real estate data. Sub-Section 3.2 shows how we use the SRISK measure to quantify the aggregated systemic risk in financial centers. Sub-Section 3.3 describes the additional control variables.

3.1 Commercial Real Estate Data

Property Market Analysis (PMA) provides annual city-level commercial real estate returns, reflecting both rental income and capital growth. We use office and retail market returns of 61 cities from 28 countries in North America, Europe, and Asia-Pacific. To the best of our knowledge, this sample contains the largest cross-section of international city-level returns over the last two decades. The panel ranges from 1995 to 2015, providing sufficient variation over time, and includes the global financial crisis period 2007/2008. For example, Real Capital Analytics (RCA) started to release international commercial real estate data in 2007, which does not provide sufficient historic returns for studying systematic differences in office market interconnectedness between normal and turmoil periods.

PMA constructs total market returns consisting of capital growth and the income component. The property price is computed from actual annual prime rents per square meter divided by the current yield taking into account depreciation and management costs. Similar to the stock market, capital growth is defined as the change between consecutive annual property values divided by the previous market value. The cash flow return, or income component, is calculated as the ratio of the annual income and the previous property value.

As a quality check, we compare our returns to the established NPI benchmark returns for commercial real estate in the United States, provided by the National Council of Real Estate Investment Fiduciaries (NCREIF).¹ At the Metropolitan Statistical Area (MSA), mean returns are comparable between PMA market data and the annualized average quarterly NPI returns. The slightly smaller standard deviation for NCREIF office market returns compared to PMA might hint at the established appraisal-based smoothing bias of the NPI index (see, e.g., Geltner (1991), Fisher, Geltner, and Webb (1994)).² In contrast, PMA returns are based on a marked-to-market valuation methodology, which raises concerns of negative autocorrelation from return reversals. However, when applying the Arellano and Bond (1991) estimator to test for autocorrelation, we find no statistically significant time lag for both return series. Furthermore, when comparing both data sources, city-level returns are highly correlated (up to 93% and 94.5% for New York and Chicago, respectively). The table suggests that a lower correlation (between 70% and 80%) can often be found in markets where the number of quarterly reported properties used by NCREIF is limited (especially in the retail sector).

In a next step, we distinguish between financial and non-financial centers. The

¹Table A.1 in the Appendix presents the results. We compare their statistical characteristics to validate that our PMA returns are qualitatively not worse than the NCREIF benchmark.

²The potential smoothing bias might also be detected when comparing the temporal return performance of both data in Figure A.1 in the Appendix. NPI retail market returns are more volatile than PMA returns, which could potentially be explained by the low number of retail properties reported to NCREIF. We conjecture that the smoothing bias is partly offset by a higher noise component. The trade-off between appraisal smoothing and transaction-based noise is well-known in the real estate literature (e.g., Geltner and Ling (2006)).

literature does not offer a unique definition of financial centers.³ We define cities as financial centers if national stock exchange trading platforms are located there. Based on this definition, our sample contains 29 financial centers.⁴ We rule out offshore financial centers, such as the Cayman Islands, the British Virgin Islands, or Jersey. Our approach is motivated by Cetorelli and Peristiani (2013) who highlight the importance of a stock exchange as a proxy for the attractiveness of a financial center. More important, following this definition, financial centers are predetermined and therefore exogenous to the office market performance. Historically, the financial service industry was built near local stock exchanges to benefit from international capital and from the floor trading access (see, e.g., Lizieri, Baum, and Scott (2000), Wójcik (2013)). In contrast, survey-based indices, such as the Global Financial Center Index (GFCI) or the Xinhua/Dow Jones International Financial Centers Development Index, rank cities based on criteria, such as infrastructure and business environment. When using these indices to identify financial centers, we would violate the exogeneity assumption, since these criteria depend on the underlying office market conditions.

Table 1 reports the summary statistics. Panel A shows mean, standard deviation, as well as minimum and maximum values for financial center and non-financial center market returns, when pooled across all cities and countries over the sample period. On average, the return performances are similar (8% for financial compared to 9% for non-financial centers). Financial centers are slightly more volatile as suggested by the standard deviation of 15% (relative to 12% for non-financial centers). Panels B and C split the sample into different sectors (office versus retail) and geographic regions (Asia-Pacific, Europe,

³Some cities dominate in specialized financial services (e.g, Zurich for wealth management). Other cities, such as Frankfurt, Hong Kong, or Singapore are considered as regional financial centers (Lizieri (2009)), whereas Wójcik (2013) identifies only London and New York as dominant global financial centers. From an economic perspective, Kindleberger (1974) defines financial centers as a concentration of financial activity where market participants gain from network effects, informational economies of scale, and direct interaction with trading partners (see also, e.g., Gehrig (2000), Lizieri (2009)).

⁴We list all cities in Table A.2 of the Appendix. Panel A indicates the market coverage of financial centers, while Panel B specifies all non-financial centers. Our empirical results also hold when we use the upper and lower tercile of cities as financial and non-financial centers, when all cities are ranked according to the average total SRISK.

and the USA), respectively. For both types of centers, office market returns indicate lower average returns accompanied by a higher standard deviation when we compare them to the within-city counterfactual retail sector. Comparing the sector performance in financial centers, the mean difference of 4%-points is statistically significant, whereas the mean difference is insignificant for non-financial centers. Geographically, mean returns differ by 3%-points (from 8% in Europe to 11% in the USA) for financial and by 4%-points (from 7% in Europe to 11% in Asia-Pacific) for non-financial centers, suggesting some regional heterogeneity.

[INSERT Table 1 HERE]

Relation to Stock Markets. We use stock market price indices that are representative for the financial center stock exchanges. For example, the listed price index for the New York Stock Exchange (NYSE) is the S&P500. We use the FTSE500 for the London Stock Exchange (LSE), or the Hang Seng Index for the Hong Kong Stock Exchange.⁵ We compute annual returns as log-differences of the price index.

We give the reader some intuition of the commercial real estate office and retail market performance. Figure 1 compares property market and stock market returns from 1995 to 2015. Panels A to C show average market returns pooled across all financial centers for the U.S., Europe, and Asia-Pacific relative to average stock market price index changes. The figures are based on local currencies to illustrate the return performance, which is unaffected by local currency movements relative to the USD.⁶ Office and retail markets follow a common cyclical pattern with the average stock market. Yet, we observe a much stronger downward trend in international office markets compared to the corresponding retail sector during the aftermath of the dotcom bubble burst in 2001/2002 and the global financial crisis period in 2007/2008. For instance, in Europe, office and retail market average returns were about 16% in 2000. However, in the subsequent years office

⁵Table A.2 of the Appendix presents the listed stock market indices and the corresponding platforms.

⁶In the empirical analysis, we then use USD-denominated returns for comparability and control for the exchange rate between the local currency and the USD.

returns fell to -2.4%, while retail returns decreased only to 7% in 2002. Similarly, U.S. office markets dropped on average from 25% in 2007 to -25% in 2009. For comparison, retail market returns decreased from 10% to -11% during the same period. From all three panels the synchronicity of the asset price bubble bursts among the regions becomes quite obvious although individual countries may deviate from the common trend.

[INSERT Figure 1 HERE]

To further establish the dynamics between stocks and office market returns in financial centers, Figure 2 illustrates impulse response functions from a panel vector autoregression (VAR). Local stock market returns tend to positively affect the related office market. The positive impact on the expected discounted rental cash flow translates into higher office market returns. During bust periods, the poor performance of the financial service industry might lead to job losses and lower demand for office space. We expect a similar relation between the stock market and the retail sector. A poor local banking sector performance might imply lower bonus payments for bankers and less income for consumption, which should also reduce the demand on the corresponding retail market. To capture the cyclical effect of the local stock market performance on both commercial real estate sectors within financial centers, we include stock market returns as an additional control variable when we test for the relation between the systemic risk of the banking sector and the office market dependence during the global financial crisis. We also analyze how a positive office market shock affects the stock market performance. The contemporaneous increase is short-living and immediately declines. We interpret this relation in terms of opportunity costs of capital, leading to higher required stock market returns, followed by a potential capital switching of investors from stocks to more attractive office property investments. However, the confidence band of the impulse response function widens and includes zero. Overall, the impulse response functions from a panel VAR suggest a Granger causality running from the stock market to the commercial real estate office markets in financial centers.

[INSERT Figure 2 HERE]

3.2 Expected Capital Shortfall

We briefly compare the Systemic Risk Measure (SRISK) of Acharya, Engle, and Richardson (2012) and Brownlees and Engle (2017) to other prominent systemic risk measures, such as the Delta Conditional Value-at-Risk (ΔCoVaR) of Adrian and Brunnermeier (2016) and the Marginal Expected Shortfall (MES) of Acharya, Pedersen, Philippon, and Richardson (2017). The ΔCoVaR takes the difference between the VaR of the financial system conditional on a particular bank being in financial distress and the VaR of the financial system given the bank is in a normal state. The MES measure captures the marginal risk contribution of a financial institution to the overall systemic risk based on its weight on the value-weighted market returns. SRISK not only takes account of the size but also of the liabilities of a financial institution. Benoit, Colliard, Hurlin, and Pérignon (2017) show that the MES measure, and thus the corresponding systemic risk ranking of financial institutions, is highly correlated with the banks' market beta and that this measure fails to forecast the contribution to systemic risk. Similarly, they illustrate that ΔCoVaR is proportional to the bank's tail risk and that the most risky institutions in terms of VaR are not inevitably the ones showing the highest systemic risk. In contrast, according to them, the relation between systematic and systemic risk is less severe for SRISK, since it includes both market capitalization and leverage.⁷

To compute the aggregated expected capital shortfall in each financial center, we use the Brownlees and Engle (2017) SRISK measure of international financial institutions

⁷Given our definition of a financial center it is important to clearly separate systemic from systematic risk. For instance, if banks specialized in similar business areas choose to be present in the same market, a shock to this respective business field will commonly affect banks operating in this specialized field. By controlling for systematic banking sector risk as well as financial center fixed effects, we rule out that return co-movements are driven by an omitted systematic risk factor and not necessarily by a systemic risk exposure.

from 2000 to 2015.⁸ The data availability of the SRISK measure also restricts the size of our sample from 2000 to 2015. SRISK quantifies the dollar-denominated expected capital shortfall of a financial institution i in period t , which would occur from a hypothetical decline of the MSCI world equity price index return by 40% or more over the next period of $h = 6$ months:

$$SRISK_{it} = E_t(CS_{i,t+h} \mid R_{MSCI,t+1,t+h} < -40\%), \quad (2)$$

with capital shortfall $CS = k(D + W) - W$, market value W , book value of debt D , prudential capital ratio k , and the multiperiod equity return between period $t + 1$ and $t + h$.⁹ Based on balance sheet information, the expected capital shortfall measures the difference between the capital reserves a financial institution must hold because of regulatory requirements or prudential management and the equity that is derived from the expected decline in the market value of the assets. We only include financial firms with a positive expected capital shortfall to focus on systemically relevant banks.

In a next step, we compute the total level of expected capital shortfall of the banking sector in the financial center. Since SRISK values are released each month, we calculate the average SRISK for each financial institution in each year. For each financial center c , we then calculate the sum of the expected capital shortfall, i.e. the individual annual *SRISK* value, of financial institutions with domestic and foreign main offices (headquar-

⁸The data is provided by the NYU Stern Volatility Lab. Table A.3 of the Appendix provides a snapshot of financial institutions with the highest SRISK level, which are measured during our sample period. For instance, the most prominent example for the financial crisis affecting the banking sector in 2008 was marked by the collapse of the investment banks Bear Stearns and Lehman Brothers (see, e.g., Brunnermeier (2009)). As indicated by Table A.3, with 57,692 million USD, Lehman Brothers had its highest expected capital shortfall in March 2008, six months prior to its insolvency in September 2008.

⁹Following Brownlees and Engle (2017), we set the prudential capital ratio equal to 8% for the U.S. and Asia-Pacific, but restrict the parameter to 5.5% for Europe. This allows us to capture differences in the Generally Accepted Accounting Principles (GAAP) for the U.S. and the International Financial Reporting Standards (IFRS) applied in Europe. However, as mentioned in their paper, the ranking of financial institutions based on their expected capital shortfall is robust to changes in parameter k .

ters, branches, or subsidiaries) in the financial center

$$SRISK_{c,t} = \sum_{i=1}^n SRISK_{it}. \quad (3)$$

To identify the main office locations of financial institutions, we use their corresponding SWIFT codes.¹⁰ Figure 3 illustrates the distribution of the financial institutions among financial centers. For instance, the largest concentration of financial institutions can be observed in London, Hong Kong, and New York.¹¹

[INSERT Figure 3 HERE]

Since the financial firms' SRISK measures are denominated in USD, we can aggregate the expected capital shortfall of the financial institutions. The denomination in USD also allows us to compare the potential undercapitalization across financial centers. Similarly, Brownlees and Engle (2017) compute the global systemic risk by aggregating the individual SRISK values of financial firms. Figure 4 illustrates the performance of the aggregated SRISK measure. In Panel A, we rank the 15 financial centers with the highest average SRISK from high (London, Hong Kong, Singapore, and New York) to low (Madrid, Amsterdam, and Luxembourg). Following the economic intuition of Brownlees and Engle (2017), our financial center-specific aggregated systemic risk can be interpreted as the required amount of capital that would be needed to bail out the related banking sector during a crisis. For instance, the SRISK value of 1,408,394 million USD for London can be interpreted as the city-specific total amount of dollar-denominated expected capital shortfall of financial institutions with domestic and foreign main offices located in this global financial center. International cities with the highest systemic risk contributed by the financial institutions' local main offices are also ranked as most relevant financial

¹⁰The SWIFT (Society for Worldwide Interbank Financial Telecommunication) established a standardized communication and service network for transactions among financial institutions. The SWIFT code contains information about the geographic location of financial institutions.

¹¹Taking into account all financial institutions, the total number of domestic and global main offices are 150 (114) for London, 120 (91) for Hong Kong, and 93 (83) for New York (when we consider financial institutions with at least two global main office locations).

centers according to the GFCI and the Xinhua/Dow Jones International Financial Centers Development Index. Panel B of Figure 4 shows the average SRISK computed from the cross-sectional city-specific levels over time. The average systemic risk of all financial centers follows an increasing trend during our sample period from 2000 to 2015 and reaches its peak in 2012.

[INSERT Figure 4 HERE]

The total amount of expected capital shortfall of systemically relevant financial institutions is significantly different between office markets in financial and non-financial centers.¹² Figure 5 illustrates the mean difference between the aggregated SRISK of both groups. On average, the total expected capital shortfall of the banking sector in financial centers equals 687,305 million USD. Office markets in non-financial centers are only exposed to an average amount of expected capital shortfall of 118,282 million USD.

[INSERT Figure 5 HERE]

3.3 Control Variables

We include several risk factors as controls. Table A.4 in the Appendix provides the definition of all variables.¹³ National GDP growth per capita and the term spread, defined as the long-term government bond yield relative to the short-term interest rate, capture macroeconomic fundamentals and the impact of the business cycle on the income-potential of commercial real estate. We add house price returns to control for the various stages of the country-specific residential real estate cycles. This is in line with the literature on the separate emergence and burst on price bubbles in the commercial and residential real estate market (Levitin and Wachter (2013), Duca and Ling (2018)). The empirical analysis

¹²To allow a clear distinction, we exclude Boston, Chicago, San Francisco, and Washington from our sample. Following our definition, these cities are identified as non-financial centers, while the GFCI ranks them among financial centers.

¹³Tables A.5 and A.6 in the Appendix show the descriptive summary and the correlation structure of the control variables.

is based on USD-denominated returns. To mitigate concerns that office market return co-movements are driven by a common exchange rate component, we control for changes of the local exchange rate relative to the USD. Exchange rate fluctuations also reflect the relative economic attractiveness of a country. At the city-level, population growth controls for systematic differences between cities. Construction rates (log-difference in floor space) in the office and retail sector capture the supply heterogeneity of building stock between both markets in a city.

We test for systemic risk as a channel between financial markets and correlated risk in private commercial real estate. We control for returns of domestic real estate investment trusts (REITs) to rule out that the correlated risk is driven by publicly listed companies, which purchase and sell properties. We include dollar-denominated MSCI world equity index returns. Since SRISK depends on the performance of the global stock market, we need to rule out that the systemic risk channel is driven by an omitted factor. Based on daily data, we calculate the yearly correlation between the local stock market return and the global MSCI world index as a proxy for financial market integration. Banks might prefer to locate their branches in financially integrated cities, which could be a potential source for related office market co-movements. We find a correlation of 30% between the total SRISK and the related financial integration level of financial centers.

We also control for the potential effect of a funding liquidity dry-up during the financial crisis on the return dependence among office markets. First, funding liquidity might be provided via structured commercial mortgage backed securities (Brunnermeier (2009), Levitin and Wachter (2013)). Therefore, we include the spread between the yields on the U.S. CMBS index and the long-term government bond as a common risk factor. More restrictive funding liquidity during periods of financial distress widens the spread because of the higher perceived default risk. Second, we capture credit supply of the banking sector (e.g., Davis and Zhu (2011)) by including international cross-border claims on each country. This variable measures the change in global dollar-denominated amounts outstanding

from the national non-bank sector (i.e., bank loans, deposits, and other instruments, such as debt securities). Third, we use changes in consumer confidence as proxy for investor sentiment (Portniaguina and Lemmon (2006), Schmeling (2009)). Consumer confidence serves as a predictor for the income potential of commercial real estate and is an ideal proxy to reflect omitted investment flows to attractive property markets.

We also disentangle the systemic risk contribution of financial institutions from their exposure to bank-specific risk factors (e.g., Begenau, Piazzesi, and Schneider (2015)). In addition to the interest rate (Term Spread) and the CMBS spread, we include the TED spread, which is computed as the difference between the LIBOR rate and the risk-free U.S. Treasury bill rate (the three month EURIBOR and the EONIA rate for the European area, respectively) as a proxy for global funding liquidity risk, especially during crisis periods when uncertainty is high (Brunnermeier (2009)).¹⁴

4 Methodology

To estimate the cross-sectional dependence between financial center office markets, we specify the following spatial econometric model:

$$r_{it} = \lambda \sum_{j \neq i} w_{ij,t} r_{jt} + X_{it} B + \eta_i + \varepsilon_{it}, \quad (4)$$

where we regress annual office market returns in financial center i in year t on the weighted average of contemporaneous office market returns in other financial centers. The weighted average $\sum_{j \neq i} w_{ij,t} r_{jt}$ is defined as the spatially lagged dependent variable. The time-varying weight $w_{ij,t}$ reflects the testable linkage mechanism between office markets i and j . The spatial lag parameter λ measures the degree of cross-sectional dependence from the

¹⁴Table A.7 of the Appendix reports regression results to show how the aggregated SRISK in financial centers is related to these bank-specific risk factors. Coefficient estimates are statistically significant for the CMBS spread as well as the short- and long-term interest rate, which are explicitly (U.S. CMBS spread) or implicitly (Term Spread, TED Spread) included as controls in our models. However, the explanatory power is rather low, ranging from 0.1 to 6%.

interconnectedness between the cross-sectional units of the endogenous variable. The set of common risk factors is captured by matrix X_{it} with parameter vector B . Parameter η_i defines individual property market fixed effects. We explicitly exploit spatial econometrics for estimating return co-movements. The spatial lag as a measure of correlated risk during crisis periods is based on first moment conditions. Hence, this methodology directly addresses the potential smoothing bias of commercial real estate data. The first moment of property market returns is not affected by the smoothing error, whereas estimates of the second and higher moments are potentially biased (see, e.g., Geltner (1991)).

We apply the Wang and Lee (2013) GMM estimator to account for the endogeneity between cross-sectional units of office market returns and the residuals, which arises from the spatial dependence structure. Their approach is flexible enough to estimate the spatial lag model with fixed effects under an unbalanced panel structure. The estimator also allows for time-varying spatial weights, which is required for our identification strategy. Following Kelejian and Prucha (2007), we use heteroscedasticity and autocorrelation consistent (HAC) standard errors that are adjusted for the dependence structure of the weighting matrix to additionally account for the potential cross-sectional correlation of the residuals.

Specification of the Weighting Matrix. We specify the spatial weighting structure to test whether the common systemic banking sector risk between financial centers implies correlated risk among their office markets. The spatial weight $w_{ij,t}$ between office market i and j is defined as

$$w_{ij,t} = \sum_l \mathbb{1}(\text{main office}_{il} \cap \text{main office}_{jl}) \times \%SRISK_{l,t}, \quad (5)$$

with the sum of binary indicator variables $\mathbb{1}$ for individual financial institutions (l), equal to one if their main offices are located in both financial centers i and j , and zero otherwise. Using the Brownlees and Engle (2017) SRISK measure, we multiply each indicator variable with the percentage SRISK ($\%SRISK_{l,t} > 0$) of the related financial institution l in

year t . The percentage SRISK captures a financial firm's contribution to the overall global systemic risk.¹⁵ The additional weighting with the %SRISK gives financial institutions with a higher systemic risk contribution a larger weight. The spatial weights model the interconnectedness between financial centers as represented by their linkage of systemically relevant financial institutions.¹⁶ We conjecture that a higher common systemic risk contribution between two financial centers, indicated by a larger spatial weight, should imply stronger co-movements between their office markets. Following our intuition, the devaluation of office properties should be stronger in financial centers with more systemically relevant banks, whereas the interconnectedness leads to simultaneous commercial real estate price declines. We also row-normalize the weights. This enables us to interpret the spatially lagged dependent variable as the weighted average of office markets. As is standard in the spatial econometric literature, we also impose $w_{ii} = 0$, such that each office market return is exposed to the weighted average of other contemporaneous office market returns, but is not directly related to itself.

The time-varying weights capture fluctuations in the expected capital shortfall over time. Panels A and B of Figure 6 illustrate the network maps for financial and non-financial centers in the crisis year 2007. The weighting structure suggests a stronger interconnectedness between financial compared to non-financial centers. Office markets are linked when financial institutions have main offices located in both financial centers. For example, the financial center Osaka is only linked to London and Tokyo (Panel A). However, their interconnectedness also depends on their common systemic risk contribution. The %SRISK only includes systemically relevant financial institutions with a positive expected capital shortfall. Hence, potential banks with main offices in Osaka

¹⁵The percentage SRISK is comparable to the established ΔCoVaR , which is based on the tail dependency between a firm and the financial system. It indicates how the systemic risk of the overall system is related to the distress of the individual institution.

¹⁶The importance of the %SRISK-weighting is further motivated in Sub-section 5.4, where we show a significant city-level office market decline when the corresponding banking sector is ranked among those with the 25% highest (compared to the 25% lowest) expected capital shortfall. Hence, we can rule out that our spatial regressions results are merely driven by the binary interconnectedness structure of the weighting matrix. The %SRISK-weighting has an additional meaning.

and other financial centers, but with a capital surplus, are not included. The network maps look similar for other sample years because of the imposed weighting structure. The interconnectedness depends on the expected capital shortfall given a hypothetical decline in the global stock market. It is essential for our identification strategy that the linkage mechanism only translates into correlated office market risk during periods of financial distress, when a valuation shock of stock market prices leads to an undercapitalization in the balance sheet of banks.

[INSERT Figure 6 HERE]

Identification Strategy. In order to isolate the common systemic banking sector risk as the source of office market co-movements, we apply a double counterfactual approach. Since the systemic risk measure in our research design is based on the expected capital shortfall, we should observe correlated risk only during the financial turmoil period 2007/2008, but not during normal times. This is in line with Brunnermeier, Rother, and Schnabel (2019) who show that the emergence of asset price bubbles leads to a higher systemic risk. Concerns might arise whether the crisis period can be considered as an exogenous event for commercial real estate markets. As discussed in Section 2, the global financial crisis 2007/2008 had its origin in the U.S. residential subprime mortgage market through which it transmitted to the international banking sector and then affected the markets for stocks and commercial real estate (see, e.g., Brunnermeier (2009) and Levitin and Wachter (2013)).

We first estimate our spatial lag model for financial center office market returns during the sample period from 2000 to 2015. However, we impose restrictions in the time-varying weighting matrix such that all spatial weights are set equal to zero during normal financial market periods. We do this by including a turmoil dummy D_{GFC} to our spatial model in Equation (4), which interacts with the spatial weight and equals 1 for the corresponding global financial crisis period 2007/2008. This model specification allows us to explicitly test for cross-sectional dependence among financial center office markets

during periods of financial distress. In addition, we conduct a placebo test to examine office market dependence during normal times. In so doing, we restrict the elements of the weighting matrix to zero during the global banking sector crisis and allow for time-varying spatial weights during normal times by resetting the turmoil dummy to 0 for the global financial crisis 2007/2008, and 1 else. Accordingly, we redefine Equation (4) into:

$$r_{it} = \lambda \sum_{j \neq i} D_{GFC} w_{ij,t} r_{jt} + X_{it} B + \eta_i + \varepsilon_{it}, \quad (6)$$

Second, we test for cross-sectional dependence among financial center retail markets during crisis periods. The retail sector serves as an ideal within-city counterfactual for the office market. Both sectors are driven by the same local market characteristics and follow a common trend. However, the retail market should not be directly exposed to the systemic banking sector risk, particularly when we control for macroeconomic fundamentals to capture potential real economic crisis effects. Hence, we should not find any empirical evidence of return co-movements among financial center retail markets. The double counterfactual approach also helps us to further disentangle the systemic risk from omitted common factors as potential transmission channel. Similarities in institutional factors, such as transparency, infrastructure as well as cultural or geographic proximity between financial centers should affect office market return co-movements not only during financial distress, but also during normal times, and should also lead to statistically significant return dependence among financial center retail markets. Likewise, assuming that international investment flows are more or less equally distributed among both property sectors in financial centers, the effect of a liquidity dry-up during crisis periods as a potential source for office market return co-movements can be rejected, since a similar effect should be observed for the within-city counterfactual retail sector.

Reflection Problem. Spatial models raise potential concerns about the reflection problem (Manski (1993)). The dependence that is captured by the weighted average of the endogenous office market returns might reflect an omitted cross-sectional dependence in

the explanatory variables. We disentangle both sources by including the equally-weighted averages of country-specific GDP growth and stock market return as additional regressors, which mirror the exogenous spatial lag structure (Sarafidis and Wansbeek (2012)).¹⁷ The endogenous spatial lag reflects the correlated risk as specified by the weighting matrix. The latter factor captures the systematic risk of explanatory variables on contemporaneous, cross-sectional units of the endogenous variable. For instance, GDP growth in country j might affect office market return in country i . In this context, we also control for the impact of global business cycle movements on commercial real estate markets (Case, Goetzmann, and Rouwenhorst (2000)).

We also include a dummy variable which is equal to 1 for the following turmoil periods: the aftermath of the dotcom bubble burst 2001/2002, the global financial crisis 2007/2008, and the European sovereign debt crisis 2010/2011. We include the crisis dummy to avoid that the counterfactual period is overlaid by any turmoil effect. This variable also ascertains that the weighting matrix for our systemic risk channel is not overlaid with the level effect on the individual market return, but captures the correlated risk. More precisely, by including the crisis dummy, we assure that the estimated co-movements between financial center office markets are driven by the proposed systemic risk channel and do not reflect a mere crisis effect.

Fixed Effects. Financial center fixed effects remove the omitted variable bias that might explain systematic differences between office markets, e.g., currency zones, gateway cities, tenant quality, quality of life, local regulation, relative size of the banking sector, or the attractiveness of a financial center. These presumably time-invariant factors might be correlated with the spatially lagged dependent variable. For example, gateway cities are particularly attractive for international investors, which should channel investment flows to these property markets. More restrictive domestic banking regulations might imply a lower demand for office space of locally active banks in the financial center. As implied

¹⁷Taking into account the dependence from explanatory variables, the specification approximates the Spatial Durbin model: $r_{it} = \lambda \sum_{j \neq i} D_{GFC} w_{ij,t} r_{jt} + X_{it} B + \delta \sum_{j \neq i} w_{ij,t} X_{jt} + \eta_i + \varepsilon_{it}$.

by the within-structure of the fixed effects specification, our model explains the variation of market returns over time within each financial center. Consequently, the spatial lag parameter can be interpreted as a measure for the degree of return co-movements between a certain financial center office market and the weighted average of contemporaneous office markets.

We do not include year dummies. The variation in the data that is left under such a two-way fixed effects specification would be the idiosyncratic component of the cross-sectional unit. Yet, we explicitly want to test for the transmission channel of spatial correlation among office markets. To capture time dummy effects, we include global factors that commonly affect all office markets.

5 Empirical Results

This section presents the empirical results. All regressions are based on USD-denominated returns to allow for comparability among international office market performance. In Sub-Section 5.1, we test for the systemic risk in financial centers as a transmission channel for return co-movements among related office markets. Sub-Section 5.2 presents additional robustness tests to support our channel. Sub-Sections 5.3 and 5.4 apply difference-in-difference models to quantify the impact on the office market performance during the global financial crisis period relative to the counterfactual retail sector and compared to non-financial center office market returns.

5.1 Systemic Risk as Transmission Channel

Table 2 shows different model specifications of Equation (6). We use Model I as the baseline model and Models II and III for robustness. Following our definition, we include all cities as financial centers in which a national stock exchange trading platform is lo-

cated.¹⁸ Our findings suggest spatial dependence among financial center office markets (*Office*) during periods of financial distress (*Turmoil*) that can be related to the common systemic risk in the banking sector. International banks are exposed to stock market fluctuations through the marked-to-market value of assets in their balance sheets. A high expected capital shortfall during financial crisis periods leads to an undercapitalization of the banking sector and might affect office markets through potential fire-sales and insolvencies in the financial service sector. At the same time investors lower their expectations on office market returns due to an expected decrease in the demand for office space, i.e. capitalization rates increase and property values depreciate. We use the global financial crisis 2007/2008 as turmoil period. We allow for a time-varying weighting matrix for these years and restrict the spatial weights to zero for the rest of the sample period. For each model specification, we find a statistically and economically significant high degree of cross-sectional dependence as implied by the spatial lag coefficient λ . Models I to III suggest return co-movements, i.e., correlated risk, with estimated spatial lag coefficients of about 29.5-33.1% during financial turmoil periods. This means that about one third of the office market performance in a financial center is affected by systemically linked financial center office markets.

We re-estimate each model to test for office market dependence during normal periods (*Normal*). Therefore, we restrict the elements of the weighting matrix to zero for the defined crisis periods and allow for time-varying weights during normal times. However, we do not observe a statistically significant spatial lag coefficient. During normal times, the expected capital shortfall of financial institutions provides only a hypothetical measure of the undercapitalization in the banking sector that would only be observed in the event of a global stock market decline. Hence, the common systemic risk in financial centers should not translate into office market return co-movements during normal times. Since

¹⁸Table A.8 in the Appendix confirms our findings, when we rank all cities according to their average systemic risk level and define the upper and lower tercile of cities as financial and non-financial centers. Top tercile SRISK cities are listed in Panel A of Figure 4, additionally including Brussels, Dublin, Vienna, and Zurich.

we find no evidence of spatial dependence among office markets during normal times, we can also rule out that the office market dependence might be related to some omitted time-invariant institutional factors during the sample period.

We also compare the dependence among office markets (*Office*) to the counterfactual within-city retail sector (*Retail*) during turmoil periods.¹⁹ Using retail market returns as the endogenous variable, we re-estimate Models I to III to test for spatial dependence during financial turmoil periods by restricting the weighting matrix to zero in normal times. Again, we do not find a statistically significant spatial lag coefficient for the within-financial center counterfactual. This supports our hypothesis that office market return co-movements might be transmitted through the common systemic banking sector risk during financial distress. For additional robustness, we also re-estimate the spatial lag for the counterfactual retail sector during normal times. As expected, the coefficient is statistically insignificant.

[INSERT TABLE 2 HERE]

The observed return dependence among financial center office markets cannot be explained by common systematic risk factors or macroeconomic fundamentals. We use contemporaneous covariates in our model to rule out that the observed spatial dependence might arise from omitted common risk factors. As can be seen from the separate regressions, the control variables receive slightly different parameter estimates for the retail and office market, suggesting different exposure of both markets to common fundamentals.

The models control for the positive relation between office markets and the underlying stock market performance within financial centers. The estimated coefficient in Model I implies that a 1%-change of stock market returns increases the local office market return by 0.09%. Correlated risk in financial center office markets prevails conditional on the relationship between stock market returns and office market performance. As expected,

¹⁹Our sample does not include retail market data for all financial centers. This explains the smaller sample for the counterfactual retail market. The cross-sectional units that are excluded can be seen in Table A.2 in the Appendix.

retail market performance is also positively related to stock market returns, which could be explained by consumption expenditures of employees from the financial service industry affecting the retail sector.

We also include the aggregated level of expected capital shortfall of the banking sector in the financial center. We find no statistically significant relation between the hypothetical capital shortfall of financial institutions located in the financial center, and the related office market. Intuitively, a higher exposure of the local office market to the expected undercapitalization of the local banking sector might have a dampening effect on expected rental cash flows. Yet, the effect is economically insignificant. We additionally control for the total expected capital shortfall to isolate the common systemic risk contribution between financial centers as the transmission channel for correlated risk of financial center office markets.²⁰ The concentration of systemic relevant banks in financial centers might increase the vulnerability of the underlying local office market during periods of financial distress. However, this effect should be reflected in the spatial lag parameter, which measures the overall return dependence among office markets during turmoil periods. During normal times, the *SRISK* level in financial centers reflects only a hypothetical effect.

We capture country-specific and local market characteristics as additional controls. Model I only includes macroeconomic fundamentals, such as GDP growth, the term spread, and the local exchange rate relative to the USD. At the city-level, population growth and the additional supply of commercial real estate capture systematic differences between cities. We find a positive and statistically significant relation between the commercial real estate and the residential housing market. National REIT market returns control for the direct channel between stock market and property market returns. As

²⁰The variable $\log(SRISK)$ differs from the transmission channel which is indicated by the weighting matrix. The aggregated *SRISK* measures the total expected capital shortfall of the local banking sector, whereas the weighting matrix reflects the interconnectedness of financial centers based on their common systemic risk contribution. Technically, the interconnectedness is based on main office locations of financial firms weighted by their *%SRISK*. We therefore can rule out that our model suffers from an overfitting.

an additional control, we include the potential return correlation of the representative national stock market with the MSCI world index as a proxy for the degree of financial integration. The variable $\Delta Claims$ reflects the potential effect on property markets coming from the international bank lending activity (e.g., Davis and Zhu (2011)).

To capture the reflection problem, we control for global GDP growth and the average global stock market return as a potential driver for the correlation among international property markets (see, e.g., Case, Goetzmann, and Rouwenhorst (2000)). Both common factors tend to positively affect commercial real estate markets. We also check the correlation of an equally-weighted global property market portfolio with global GDP growth (69% for office and 77% for retail) and the average stock market return (65% for office and 69% for retail). Our findings suggest that both common factors might capture some of the variation coming from an omitted global CAPM market factor for commercial real estate. However, to fully preclude that our spatial weights reflect the impact of the overall property market portfolio, we provide an additional robustness test: We first separately regress office and retail market returns on the corresponding global market portfolio (with estimated beta coefficients of 1.15 and 1.17 for the office and retail sector, respectively). In a second step, we then use the residuals as endogenous variable to replicate the results of the spatial lag models in Table A.9 of the Appendix. We still find evidence of cross-sectional dependence among financial center office markets during the global financial crisis, whereas the spatial lags are statistically insignificant for office markets during normal times and for the counterfactual retail sector during the crisis and normal periods. We conclude that correlated risk does not merely reflect a global property market portfolio, but can be explained by the systemic risk channel and the interconnectedness of the financial system.

The main results hold, when we include additional control variables. Model II also includes the exposure of commercial real estate markets to the performance of mortgage-backed securities and investor sentiment. We find a positive relation between office market

returns and the U.S. CMBS spread, which can be interpreted in terms of higher risk premiums. Our findings suggest that a decline in investor confidence increases office market returns in financial centers. This is in line with our intuition that investors require higher returns as a compensation for holding less attractive income-producing properties. Model III additionally captures the overall global interbank credit risk as reflected in the TED spread (Brunnermeier (2009)). A widened spread reflects a higher default risk of the banking sector and can be interpreted as a dry-up of funding liquidity, which lowers the office market performance.

5.2 Robustness Tests

Non-Financial Centers. We first re-estimate the spatial regression models using only non-financial center office markets. Since the expected capital shortfall of the banking sector in non-financial centers is significantly smaller than in financial centers, office markets in these cities should be less vulnerable to the global systemic risk during periods of financial distress. Table 3 reports the coefficient estimates. We find no statistically significant effect of office market co-movements implied by the common banking sector risk in our model specifications. Following our criterion of how we define financial centers, our sample of non-financial centers also includes the cities Boston, Chicago, San Francisco, and Washington. These cities are ranked among the top 15 financial centers according to the GFCI but do not host national stock exchanges. Before estimating the model, we therefore exclude these four cities from our sample.²¹

[INSERT TABLE 3 HERE]

MSCI World Index as Common Factor. A potential concern could also be that our transmission channel reflects the common effect of the MSCI world equity index on international commercial real estate in financial centers. By construction, the

²¹Table A.8 in the Appendix confirms our results when we use cities from the bottom tercile with the lowest SRISK level, also including the cities Boston, Chicago, and Washington.

SRISK measure of financial institutions depends on the performance of the global equity market. In Table 4, we re-estimate the spatial model for financial and non-financial centers when we include global MSCI world equity index returns as an additional control variable instead of national stock market returns. We show that even after controlling for the global equity market performance, our transmission channel of common systemic risk contribution among financial centers prevails and implies statistically significant return co-movements among the related office markets during turmoil periods. The estimated coefficients of the spatial model are qualitatively the same. As expected, we find no evidence of office market dependence among non-financial centers.²²

[INSERT TABLE 4 HERE]

Placebo Tests from Other Crisis Periods. Table 5 tests for correlated risk in financial center office markets during the European sovereign debt crisis and the dotcom bubble burst. We use both crisis periods as a placebo test to show that our transmission channel is related to systemic risk. Applying the same identification strategy, we allow the spatial weights to vary during turmoil periods and restrict them to zero during normal times. We compare spatial dependence across financial center office markets with the counterfactual retail sector during the crisis periods 2010 and 2011. As expected, the results reveal no correlated risk, when the European sovereign debt crisis hit the banking sector. The origin of the sovereign debt crisis was mainly confined to Ireland and Southern European countries, such as Italy, Portugal, Spain, and particularly Greece. The crisis was immediately followed by specific bailout strategies for local banks to prevent spillover effects to the overall financial banking sector (Lane (2012)).

We also find no evidence of correlated risk during the dotcom bubble burst in 2000/2001. This result is in line with Aoki and Nikolov (2015) who argue that the impact of asset price bubbles on systemic risk depends on the type of economic agents

²²We do not control for stock market integration when re-estimating the spatial models for non-financial centers as they do not host national stock exchange trading platforms.

that are exposed to these bubbles. Mainly ordinary savers suffered a financial loss without spillovers to the rest of the economy. However, when banks hold exposure to overvalued assets, an asset price bubble collapse, such as the one at the U.S. housing market in 2007, devastates the equity of the financial system. The bank exposures to bubbles are the reasons why the dotcom bubble did not result in a banking crisis, while the subprime mortgage crisis did.

[INSERT TABLE 5 HERE]

5.3 Office versus Retail: Evidence from Difference-in-Difference

Sub-section 5.1 shows empirical evidence of cross-sectional dependence among office markets during the global financial crisis period. The spatial models capture the effect of the immediate valuation shock triggered through the systemic risk channel. In order to quantify the entire effect the crisis has on commercial real estate markets in the aftermath period 2008/2009, we apply a difference-in-difference model. If the common systemic risk in the banking sector negatively affects the office market performance in financial centers, we should also observe a significant return decline relative to the counterfactual retail sector during periods of financial distress, when asset prices fall. In this quasi-experimental setting, we exploit the global financial crisis period to compare the return performance of both sectors within financial centers. We specify the following linear difference-in-difference model

$$r_{it} = \beta_0 + \beta_1 D_{Crisis} + \beta_2 D_{Office} + \beta_3 (D_{Crisis} \times D_{Office}) + X_{it}\beta + \epsilon_{it}, \quad (7)$$

with property market returns r_{it} in year t regressed on the dummy variable for the period of the financial crisis aftermath, D_{Crisis} , the office market dummy, D_{Office} , and their interaction conditional on a set of control variables X_{it} . The pre-crisis period ranges from 2005 to 2007. The years 2008 and 2009 resemble the aftermath of the financial crisis,

for which we set the crisis dummy equal to 1. Given the within-city comparison between affected and counterfactual markets, which should be driven by common factors, we can rule out that the required common trend assumption might be violated.

Model I of Table 6 shows a statistically significant coefficient for the interaction term between the crisis aftermath 2008/2009 and the office market dummy. The negative coefficient of -0.11 suggests an average decrease in office market returns compared to the counterfactual retail sector during the aftermath of the global financial crisis. Common factors are removed by the difference-in-difference structure. Model II additionally controls for systematic differences in the supply of floor space between both sectors, which is measured in levels.

We also replicate the difference-in-difference model for the sovereign debt crisis and the dotcom bubble burst. To analyze the impact of the European sovereign debt crisis, we split the sample into a pre-crisis period from 2005 to 2009 before the bubble burst, including a dummy to capture the impact of the global financial crisis 2007/2008, and the subsequent turmoil by setting the crisis-dummy to 1 for the years 2010 and 2011. We restrict the crisis periods to two years to estimate the aftermath effect immediately after the bubble burst. We find no statistically significant impact of the turmoil period on office market returns relative to the retail sector. For the dotcom bubble burst, we use a sample from 1995 to 2002 with the crisis dummy equal to 1 for 2001 and 2002 to capture the aftermath of the bubble burst. We find a significant impact of -0.081 on financial center office markets relative to the retail sector. The coefficient is slightly smaller than the estimated effect for the global financial crisis. While the spatial models indicate that this effect is not driven by the systemic risk channel, the return decline in the financial sector could be related to a reduction in demand for stock exchange services.

[INSERT TABLE 6 HERE]

5.4 Financial versus Non-Financial Center Office Markets

We also compare office market returns between financial and non-financial centers. To clearly distinguish between them, we exclude Boston, Chicago, San Francisco, and Washington from our sample. We follow the same difference-in-difference methodology of the previous sub-section. However, because of data limitations, we do not have sufficient city-level controls to capture all differences between financial and non-financial centers. Therefore, the intention of this robustness test is not to make any causal statement but to use the difference-in-difference model as a mean comparison approach between both office market types.

Table 7 suggests 13% lower office market returns in financial than in non-financial centers during the aftermath of the global crisis. We find no significant mean difference for the sovereign debt crisis 2010/2011 or the aftermath of the dotcom bubble burst. Overall, the findings are similar when we control for the supply of office market floor space and city-level population growth (Model II) and additional national macroeconomic control variables to remove potential differences between financial and non-financial centers located in different countries (Model III).

[INSERT TABLE 7 HERE]

Motivated by the results of Table 7, we extend our analysis on office market returns during the aftermath of the global financial crisis in the years 2008 and 2009. From Figure 5, we conclude that the total SRISK is systematically higher in financial than in non-financial centers. Table 8 shows that, conditional on a global financial crisis dummy, office market returns are not significantly lower in cities with a higher expected capital shortfall, both in terms of a level effect (Model I) and its growth rate (Model II). However, Models III to V indicate that the decrease in office market returns during the financial

crisis period is stronger in cities with a higher total SRISK.²³

We distinguish between office markets in the sample for which the aggregated SRISK in the banking sector belongs either to the 25% highest or the 25% lowest each year. We specify dummy variables for both quartiles (*SRISK_{high}* and *SRISK_{low}*) and interact them with the year dummies of 2008 and 2009 to capture the aftermath effect of the financial crisis. On average, office market returns decrease by 12% in those years (Model IV). In contrast, the magnitude equals -22% for office markets in cities with a banking sector that belongs to the group with the 25% highest expected capital shortfall. However, we find no statistically significant stronger effect for office markets of cities with the lowest 25% expected capital shortfall. We conclude that during normal times a higher expected capital shortfall does not have a significant impact on office market returns. However, a higher potential undercapitalization in the banking sector increases the vulnerability of the underlying office market during periods of financial distress. This effect is the stronger the higher the undercapitalization in a banking sector of a financial center.

[INSERT TABLE 8 HERE]

6 Conclusion

This paper tests for the common systemic risk contribution of financial firms between local banking sectors as a source of return co-movements among international financial center office markets. The systemic banking sector risk reflects the potential undercapitalization of financial institutions given a hypothetical decline in the performance of global equity markets. Hence, we test for cross-sectional dependence among financial center office markets during financial turmoil periods, when a substantial decline in stock market prices has an immediate impact on the balance sheets of financial firms. We exploit the global

²³Because we are interested in the cross-sectional variation of market returns, we do not include individual fixed effects. Similarly, year fixed effects are also not considered. This enables us to assess the impact of the financial crisis dummy on the cross-sectional differences between office markets.

financial crisis in 2007/2008 as a banking crisis with substantial exposure to the U.S. housing market bubble. Our identification strategy is based on a double counterfactual approach, which contrasts crisis with non-crisis periods as well as the office with the retail sector within financial centers. We also apply placebo tests for spatial dependence among financial center office markets during normal times and among the counterfactual retail markets.

We find empirical evidence of return co-movements among financial center office markets during financial crisis periods which can be related to the common systemic banking sector risk. As expected, the return dependence among office markets cannot be observed during normal times. Our findings further suggest no return co-movements among financial center retail markets or among non-financial center office markets. We also compare the office market return performance between financial and non-financial centers during the aftermath of the global financial crisis. The results indicate a negative impact on the return performance, which is stronger for financial center office markets. This is in line with our economic intuition: the total expected capital shortfall is significantly larger in financial than in non-financial centers, which increases the fragility of the related office markets during periods of financial distress.

Our findings reveal new insights into the vulnerability of international commercial real estate markets in financial centers that can be related to the systemic risk of the banking sector. Even more important, we provide implications for international investors with respect to diversification potentials and the related risk management of their portfolios. The correlated risk between financial center office markets and the stock markets performance during financial turmoil reduces diversification potentials both within international financial center office markets and across office and stock markets.

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Table 1: Summary Statistics of Commercial Real Estate Market Returns

This table contains the descriptive summary for commercial real estate market returns. Our sample is pooled over a cross-section of 61 cities in 28 countries from 2000 to 2015. This sample restriction is in line with the data availability of the SRISK measure and corresponds to the sample we use in the analysis. We define all cities with a stock exchange trading platform as financial center. Panel A distinguishes between financial and non-financial centers. Panels B and C additionally separate market returns by sectors and geographic regions, respectively. Returns are calculated as log-differences. The values are measured in decimals.

Panel A: Financial versus Non-Financial Center					
	Mean	Std.Dev.	Min.	Max.	Obs.
Financial	0.08	0.15	-0.70	0.79	1048
Non-Financial	0.09	0.12	-0.44	0.65	1139
Panel B: Market Returns by Sector					
	Mean	Std.Dev.	Min.	Max.	Obs.
Financial					
Office	0.07	0.16	-0.56	0.79	581
Retail	0.11	0.15	-0.70	0.71	467
Non-Financial					
Office	0.08	0.13	-0.44	0.65	644
Retail	0.09	0.10	-0.24	0.60	495
Panel C: Market Returns by Geographic Region					
	Mean	Std.Dev.	Min.	Max.	Obs.
Financial					
Asia-Pacific	0.09	0.19	-0.64	0.71	233
Europe	0.08	0.14	-0.70	0.79	733
USA	0.11	0.15	-0.52	0.39	42
Non-Financial					
Asia-Pacific	0.11	0.15	-0.28	0.65	152
Europe	0.07	0.11	-0.33	0.60	588
USA	0.09	0.12	-0.44	0.49	399

Table 2: Correlated Risk among Financial Center Office Markets

This table shows the results of spatial models for office and retail markets in *financial centers* from 2000 to 2015. As *Turnmoil* period, we use the financial crisis period 2007/2008. To measure spatial dependence during the turmoil period, the elements of the weighting matrix are restricted to zero for *normal* times. To measure dependence during normal times, we restrict the weighting matrix to zero for the crisis period. The Pesaran (2004) CD test shows *t*-statistics of the null hypothesis of residual independence. Spatial HAC-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Model I						Model II						Model III					
	Office			Retail			Office			Retail			Office			Retail		
	Turnmoil	Normal		Turnmoil	Normal		Turnmoil	Normal		Turnmoil	Normal		Turnmoil	Normal		Turnmoil	Normal	
Spatial Lag	0.295** (0.145)	-0.510 (0.624)	-0.096 (0.140)	0.109 (0.111)	0.325** (0.139)	-0.487 (0.993)	0.325** (0.139)	0.109 (0.140)	0.325** (0.139)	-0.487 (0.993)	0.011 (0.147)	0.331** (0.146)	-0.534 (1.086)	-0.011 (0.157)	0.020 (0.147)			
Stock Returns	0.093** (0.047)	0.105* (0.057)	0.080* (0.044)	0.083* (0.043)	0.083* (0.043)	0.091* (0.050)	0.083* (0.043)	0.083* (0.043)	0.091* (0.050)	0.077* (0.044)	0.078* (0.044)	0.081* (0.043)	0.090* (0.051)	0.076* (0.044)	0.078* (0.044)			
log(SRISK)	-0.010 (0.011)	-0.010 (0.014)	-0.006 (0.010)	-0.007 (0.010)	-0.014 (0.010)	-0.016 (0.015)	-0.014 (0.010)	-0.006 (0.010)	-0.016 (0.015)	-0.008 (0.010)	-0.008 (0.010)	-0.015 (0.010)	-0.018 (0.013)	-0.008 (0.010)	-0.008 (0.010)			
ΔGDP Capita	0.663*** (0.182)	0.813*** (0.203)	0.835*** (0.190)	0.813*** (0.187)	0.622*** (0.172)	0.756*** (0.185)	0.622*** (0.172)	0.813*** (0.187)	0.622*** (0.172)	0.756*** (0.185)	0.810*** (0.186)	0.507*** (0.176)	0.586*** (0.187)	0.803*** (0.190)	0.800*** (0.190)			
Term Spread	0.248 (0.499)	0.249 (0.722)	1.047* (0.586)	0.998* (0.579)	0.046 (0.477)	-0.076 (0.585)	0.046 (0.477)	0.998* (0.579)	0.046 (0.477)	-0.076 (0.585)	1.056* (0.590)	0.150 (0.466)	0.092 (0.652)	1.075* (0.588)	1.060* (0.588)			
ΔFloor Space	-0.884*** (0.303)	-1.070*** (0.325)	0.019 (0.163)	0.015 (0.161)	-0.723** (0.294)	-0.841*** (0.312)	-0.723** (0.294)	0.019 (0.163)	-0.723** (0.294)	-0.841*** (0.312)	0.047 (0.165)	-0.767*** (0.290)	-0.918*** (0.295)	0.048 (0.166)	0.045 (0.165)			
ΔREIT	0.351 (0.240)	0.697** (0.352)	-0.138 (0.281)	-0.152 (0.277)	0.199 (0.224)	0.463 (0.288)	0.199 (0.224)	-0.138 (0.281)	0.199 (0.224)	0.463 (0.288)	-0.175 (0.282)	0.167 (0.217)	0.441 (0.372)	-0.171 (0.284)	-0.172 (0.283)			
ΔPopulation	0.077 (0.118)	0.091 (0.144)	0.661 (0.845)	0.600 (0.846)	0.065 (0.104)	0.071 (0.123)	0.065 (0.104)	0.661 (0.845)	0.065 (0.104)	0.071 (0.123)	0.823 (0.844)	0.085 (0.112)	0.105 (0.137)	0.859 (0.848)	0.832 (0.849)			
ΔResidential	0.619*** (0.174)	0.677*** (0.193)	0.465*** (0.120)	0.464*** (0.119)	0.596*** (0.159)	0.654*** (0.171)	0.596*** (0.159)	0.465*** (0.120)	0.596*** (0.159)	0.654*** (0.171)	0.476*** (0.119)	0.576*** (0.157)	0.629*** (0.170)	0.475*** (0.119)	0.474*** (0.119)			
Correlation to MSCI	0.087 (0.066)	0.099 (0.078)	0.103* (0.060)	0.112* (0.060)	0.077 (0.064)	0.082 (0.075)	0.077 (0.064)	0.103* (0.060)	0.077 (0.064)	0.082 (0.075)	0.101* (0.061)	0.087 (0.062)	0.099 (0.072)	0.102* (0.061)	0.103* (0.061)			
ΔClaims	0.008 (0.050)	-0.021 (0.069)	0.006 (0.064)	0.007 (0.063)	0.014 (0.048)	-0.004 (0.060)	0.014 (0.048)	0.006 (0.063)	0.014 (0.048)	-0.004 (0.060)	0.008 (0.064)	0.004 (0.045)	-0.023 (0.070)	0.006 (0.063)	0.007 (0.063)			
ΔSentiment					-0.006*** (0.001)	-0.006*** (0.002)	-0.006*** (0.001)		-0.006*** (0.001)	-0.006*** (0.002)	0.0004 (0.001)	-0.006*** (0.002)	-0.007*** (0.002)	0.0004 (0.001)	0.0004 (0.001)			
U.S. CMBS Spread					0.086*** (0.016)	0.128 (0.100)	0.086*** (0.016)		0.086*** (0.016)	0.128 (0.100)	0.025 (0.015)	0.074*** (0.015)	0.113 (0.096)	0.024 (0.015)	0.023 (0.016)			
TED Spread												-3.015** (0.772)	-4.842** (2.230)	-0.233 (0.828)	-0.199 (0.841)			
ΔGDP	0.407* (0.215)	1.205 (0.312)	0.423* (0.247)	0.315 (0.267)	0.309 (0.199)	0.995 (1.103)	0.309 (0.199)	0.423* (0.247)	0.315 (0.267)	0.995 (1.103)	0.392 (0.284)	0.355 (0.197)	1.146 (1.414)	0.411 (0.253)	0.392 (0.300)			
Stock Returns	0.090 (0.067)	0.195*** (0.067)	0.146*** (0.056)	0.118** (0.050)	0.079 (0.065)	0.195*** (0.058)	0.079 (0.065)	0.146*** (0.056)	0.118** (0.050)	0.195*** (0.058)	0.123** (0.056)	0.043 (0.068)	0.142** (0.063)	0.124** (0.060)	0.120** (0.050)			
Crisis Dummy	-0.002 (0.024)	-0.0003 (0.078)	-0.021 (0.020)	-0.020 (0.019)	-0.039 (0.024)	-0.045 (0.099)	-0.039 (0.024)	-0.021 (0.020)	-0.020 (0.019)	-0.045 (0.099)	-0.036 (0.021)	-0.034 (0.024)	-0.041 (0.105)	-0.035 (0.022)	-0.035 (0.023)			
ΔExchange Rate	-0.572 (0.443)	-1.457** (0.726)	-0.061 (0.465)	-0.018 (0.457)	-0.239 (0.422)	-0.955* (0.517)	-0.239 (0.422)	-0.061 (0.465)	-0.018 (0.457)	-0.955* (0.517)	0.037 (0.470)	-0.092 (0.406)	-0.799 (0.712)	0.038 (0.471)	0.039 (0.468)			
Observations	464	464	368	368	464	464	464	368	464	464	368	464	464	368	368			
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Pesaran CD	11.99***	24.95***	5.55***	4.18***	10.01***	20.71***	10.01***	5.24***	5.10***	6.17***	15.20***	5.05***	15.20***	4.83***	4.83***			
Adj.-R ²	0.486	0.446	0.521	0.525	0.529	0.497	0.529	0.517	0.517	0.549	0.528	0.516	0.528	0.517	0.517			

Table 3: Correlated Risk among Non-Financial Center Office Markets

This table shows the results of spatial models for office and retail markets in *non-financial centers* from 2000 to 2015. As *Turnoil* period, we use the financial crisis period 2007/2008. To measure spatial dependence during the turmoil period, the elements of the weighting matrix are restricted to zero for *normal* times. To measure dependence during normal times, we restrict the weighting matrix to zero for the crisis period. The Pesaran (2004) CD test shows *t*-statistics of the null hypothesis of residual independence. Spatial HAC-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Model I				Model II				Model III			
	Office		Retail		Office		Retail		Office		Retail	
	Turnoil	Normal	Turnoil	Normal	Turnoil	Normal	Turnoil	Normal	Turnoil	Normal	Turnoil	Normal
Spatial Lag	-0.135 (0.191)	0.121 (0.128)	-0.155 (0.180)	0.128 (0.126)	-0.058 (0.197)	0.097 (0.106)	-0.100 (0.185)	0.126 (0.128)	-0.011 (0.202)	0.052 (0.125)	-0.014 (0.195)	0.102 (0.128)
Stock Returns	0.057 (0.044)	0.053 (0.044)	0.061 (0.047)	0.056 (0.049)	0.047 (0.044)	0.045 (0.044)	0.055 (0.048)	0.053 (0.049)	0.038 (0.046)	0.038 (0.045)	0.046 (0.048)	0.049 (0.049)
log(SRISK)	-0.001 (0.002)	-0.002 (0.003)	0.002 (0.003)	0.001 (0.003)	-0.001 (0.002)	-0.002 (0.002)	0.001 (0.003)	0.001 (0.003)	-0.002 (0.002)	-0.002 (0.003)	0.001 (0.003)	0.001 (0.003)
Δ GDP Capita	1.154*** (0.183)	1.118*** (0.174)	0.335*** (0.160)	0.327*** (0.157)	1.120*** (0.175)	1.095*** (0.169)	0.325*** (0.163)	0.320*** (0.161)	1.063*** (0.176)	1.055*** (0.173)	0.300* (0.167)	0.302* (0.167)
Term Spread	-1.194** (0.582)	-1.098** (0.526)	0.343 (0.474)	0.341 (0.438)	-1.114* (0.614)	-1.094** (0.557)	0.375 (0.568)	0.347 (0.529)	-0.967 (0.624)	-0.984* (0.576)	0.547 (0.568)	0.439 (0.520)
Δ Floor Space	-1.198*** (0.277)	-1.178*** (0.276)	-0.244 (0.201)	-0.259 (0.206)	-1.125*** (0.265)	-1.114*** (0.268)	-0.244 (0.199)	-0.250 (0.204)	-1.065*** (0.261)	-1.062*** (0.265)	-0.236 (0.198)	-0.233 (0.203)
Δ REIT	0.368 (0.331)	0.258 (0.315)	0.663** (0.328)	0.684** (0.323)	0.188 (0.334)	0.136 (0.318)	0.574* (0.347)	0.616* (0.340)	0.371 (0.325)	0.331 (0.322)	0.628* (0.346)	0.664** (0.338)
Δ Population	1.581** (0.731)	1.507** (0.717)	1.231* (0.733)	1.177 (0.725)	1.535** (0.708)	1.503** (0.701)	1.265* (0.742)	1.205 (0.733)	1.573** (0.713)	1.550** (0.706)	1.285* (0.735)	1.241* (0.730)
Δ Residential	0.165 (0.114)	0.172 (0.110)	0.463*** (0.105)	0.468*** (0.103)	0.190* (0.111)	0.188* (0.107)	0.475*** (0.101)	0.472*** (0.100)	0.163 (0.112)	0.163 (0.109)	0.468*** (0.102)	0.461*** (0.100)
Δ Claims	0.105** (0.045)	0.113 (0.044)	0.083* (0.048)	0.077 (0.048)	0.136** (0.045)	0.139*** (0.045)	0.094* (0.050)	0.086* (0.050)	0.118** (0.046)	0.121*** (0.046)	0.086* (0.050)	0.082* (0.050)
Δ Sentiment					-0.293 (0.607)	-0.247 (0.600)	-0.054 (0.592)	-0.100 (0.590)	-0.051 (0.598)	-0.055 (0.600)	-0.004 (0.593)	-0.051 (0.594)
U.S. CMBS Spread					0.057*** (0.013)	0.050*** (0.014)	0.020* (0.012)	0.016 (0.012)	0.050*** (0.014)	0.047*** (0.015)	0.016 (0.012)	0.013 (0.012)
TED Spread									-1.271** (0.639)	-1.149* (0.693)	-0.776 (0.528)	-0.582 (0.527)
$\Delta \overline{GDP}$	0.123 (0.278)	-0.008 (0.276)	0.511* (0.287)	0.469* (0.279)	-0.057 (0.284)	-0.130 (0.281)	0.426 (0.317)	0.398 (0.307)	0.178 (0.292)	0.119 (0.314)	0.518 (0.323)	0.480 (0.318)
<i>StockReturns</i>	0.189*** (0.061)	0.171*** (0.054)	0.118** (0.056)	0.109** (0.052)	0.184*** (0.058)	0.176*** (0.052)	0.118** (0.056)	0.111** (0.051)	0.157*** (0.061)	0.157*** (0.054)	0.102* (0.059)	0.103** (0.052)
Crisis Dummy	0.049** (0.020)	0.043*** (0.015)	0.023 (0.017)	0.022 (0.015)	0.025 (0.022)	0.025 (0.017)	0.015 (0.019)	0.017 (0.016)	0.026 (0.022)	0.026 (0.017)	0.013 (0.019)	0.017 (0.016)
Δ Exchange Rate	-0.965* (0.543)	-0.752 (0.515)	-0.724 (0.564)	-0.767 (0.577)	-0.598 (0.537)	-0.498 (0.509)	-0.556 (0.594)	-0.638 (0.586)	-0.885* (0.527)	-0.815 (0.516)	-0.634 (0.594)	-0.705 (0.581)
Observations	416	416	304	304	416	416	304	304	416	416	304	304
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pesaran CD	5.55***	4.14***	3.81***	2.48***	3.34***	2.56***	3.62***	2.32***	2.12**	1.85*	2.61***	1.78*
Adj.-R ²	0.538	0.549	0.560	0.567	0.556	0.564	0.557	0.562	0.560	0.563	0.558	0.562

Table 4: Correlated Risk Conditional on MSCI World Index

This table shows the results of spatial models for office and retail markets in financial and non-financial centers from 2000 to 2015. As *Turmoil* period, we use the financial crisis period 2007/2008. To measure spatial dependence during the turmoil period, the elements of the weighting matrix are restricted to zero for *normal* times. To measure dependence during normal times, we restrict the weighting matrix to zero for the crisis period. The Pesaran (2004) CD test shows *t*-statistics of the null hypothesis of residual independence. Spatial HAC-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Financial Centers				Non-Financial Centers			
	Office		Retail		Office		Retail	
	Turmoil	Normal	Turmoil	Normal	Turmoil	Normal	Turmoil	Normal
Spatial Lag	0.369*** (0.112)	-0.390 (0.271)	0.103 (0.138)	0.112 (0.138)	0.195 (0.182)	-0.015 (0.111)	0.096 (0.111)	0.072 (0.121)
Stock Return	0.090** (0.037)	0.154*** (0.033)	0.124*** (0.042)	0.143*** (0.039)	0.088** (0.040)	0.106*** (0.034)	0.079** (0.034)	0.091** (0.036)
log(SRISK)	-0.027*** (0.010)	-0.033*** (0.011)	-0.015 (0.011)	-0.013 (0.011)	-0.003 (0.002)	-0.002 (0.002)	0.0004 (0.002)	0.001 (0.003)
Δ GDP Capita	0.354** (0.164)	0.326* (0.173)	0.629*** (0.177)	0.632*** (0.177)	0.982*** (0.171)	0.988*** (0.172)	0.255 (0.172)	0.258* (0.157)
Term Spread	0.113 (0.385)	0.117 (0.410)	1.380** (0.559)	1.120* (0.577)	-0.809 (0.573)	-1.028* (0.566)	0.614 (0.566)	0.423 (0.504)
Δ Floor Space	-0.638** (0.279)	-0.775*** (0.283)	0.041 (0.170)	0.010 (0.165)	-1.040*** (0.229)	-1.033*** (0.231)	-0.217 (0.231)	-0.194 (0.228)
Δ REIT	-0.219 (0.218)	-0.178 (0.223)	-0.342 (0.290)	-0.328 (0.285)	-0.034 (0.308)	0.035 (0.317)	0.281 (0.317)	0.351 (0.317)
Δ Population	0.073 (0.081)	0.078 (0.084)	0.661 (0.857)	0.587 (0.869)	1.199* (0.727)	1.251* (0.736)	1.082 (0.736)	1.070 (0.733)
Δ Residential	0.517*** (0.142)	0.542*** (0.146)	0.472*** (0.115)	0.460*** (0.117)	0.143 (0.112)	0.123 (0.111)	0.448*** (0.111)	0.432*** (0.101)
Δ Claims	0.051 (0.046)	0.071 (0.051)	0.040 (0.066)	0.046 (0.064)	0.187*** (0.047)	0.191*** (0.047)	0.146*** (0.047)	0.142*** (0.052)
Δ Sentiment	-0.006*** (0.002)	-0.006*** (0.002)	0.001 (0.001)	0.0004 (0.001)	0.858 (0.049)	0.882 (0.647)	0.667 (0.647)	0.640 (0.662)
Correlation to MSCI	0.110* (0.061)	0.128* (0.071)	0.126** (0.062)	0.139** (0.061)				
U.S. CMBS Spread	0.052*** (0.015)	0.070*** (0.021)	0.010 (0.016)	0.006 (0.015)	0.039*** (0.014)	0.037*** (0.014)	0.005 (0.014)	0.002 (0.012)
TED Spread	-1.235 (0.798)	-2.166*** (0.826)	0.282 (0.859)	0.366 (0.862)	-0.302 (0.712)	-0.266 (0.712)	0.192 (0.712)	0.323 (0.569)
$\Delta \overline{GDP}$	-0.270 (0.223)	0.127 (0.286)	0.210 (0.276)	0.138 (0.288)	-0.252 (0.294)	-0.190 (0.313)	0.097 (0.313)	0.113 (0.299)
Δ MSCI World	0.197*** (0.038)	0.272*** (0.074)	0.102** (0.040)	0.090** (0.044)	0.133*** (0.029)	0.134*** (0.032)	0.113*** (0.032)	0.108*** (0.029)
Crisis Dummy	-0.046*** (0.017)	-0.049* (0.027)	-0.059*** (0.019)	-0.040* (0.021)	0.001 (0.018)	0.009 (0.015)	-0.001 (0.015)	0.007 (0.016)
Δ Exchange Rate	0.880** (0.439)	0.718 (0.452)	0.546 (0.509)	0.478 (0.495)	-0.049 (0.521)	-0.186 (0.528)	0.054 (0.528)	-0.081 (0.619)
Observations	464	464	368	368	416	416	304	304
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pesaran CD	6.56***	11.66***	4.74***	3.91***	1.68*	1.68*	1.05	0.44
Adj.- R^2	0.577	0.563	0.519	0.524	0.572	0.568	0.573	0.574

Table 5: Placebo Test on Alternative Crisis Periods

This table shows the results of spatial models for office and retail markets in financial centers from 2000 to 2015. As *Turmoil* period, we use the sovereign debt crisis period 2010/2011 and the dotcom bubble burst 2000/2001, respectively. To measure spatial dependence during the turmoil period, the elements of the weighting matrix are restricted to zero for *normal* times. To measure dependence during normal times, we restrict the weighting matrix to zero for the crisis period. The Pesaran (2004) CD test shows *t*-statistics of the null hypothesis of residual independence. Spatial HAC-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Sovereign Debt Crisis 2010-2011		Dotcom Bubble Burst 2000-2001	
	Turmoil		Turmoil	
	Office	Retail	Office	Retail
Spatial Lag	0.381 (0.235)	0.052 (0.167)	0.584 (0.711)	-4.797 (3.627)
Stock Returns	0.100** (0.045)	0.079* (0.044)	0.091** (0.046)	0.091** (0.044)
log(SRISK)	-0.016 (0.012)	-0.008 (0.011)	-0.005 (0.013)	-0.042 (0.028)
Δ GDP Capita	0.661*** (0.179)	0.827*** (0.189)	0.668*** (0.184)	0.866*** (0.213)
Term Spread	-0.138 (0.488)	1.125** (0.566)	0.056 (0.467)	1.139** (0.550)
Δ Floor Space	-0.952*** (0.297)	0.027 (0.162)	-0.962*** (0.305)	-0.028 (0.876)
Δ REIT	0.261 (0.236)	-0.146 (0.285)	0.319 (0.243)	-0.109 (0.281)
Δ Population	0.076 (0.128)	0.674 (0.844)	0.070 (0.130)	0.208 (0.876)
Δ Residential	0.595*** (0.173)	0.471*** (0.118)	0.612*** (0.172)	0.442*** (0.130)
Correlation to MSCI	0.075 (0.066)	0.101* (0.061)	0.028 (0.049)	-0.014 (0.063)
Δ Claims	0.043 (0.050)	0.005 (0.065)	0.081 (0.066)	0.105* (0.059)
$\Delta \overline{GDP}$	0.280 (0.191)	0.429* (0.248)	0.314 (0.247)	0.275 (0.298)
$\overline{StockReturns}$	0.165*** (0.056)	0.120** (0.051)	0.196*** (0.055)	0.093* (0.053)
Crisis Dummy	0.009 (0.024)	-0.033 (0.021)	0.040* (0.023)	-0.019* (0.026)
Δ Exchange Rate	-0.440 (0.448)	-0.030 (0.475)	-0.538 (0.466)	-0.177 (0.459)
Observations	464	368	464	368
Fixed Effects	Yes	Yes	Yes	Yes
Pesaran CD	12.74***	5.54***	12.63***	5.66***
Adj.- R^2	0.489	0.519	0.502	0.542

Table 6: Difference-in-Difference Model: Office versus Retail

This table shows the regression result of the difference-in-difference model for financial centers. We regress property market returns r_{it} on the dummy variable for the financial crisis period, D_{Crisis} , the office market dummy, D_{Office} , and their interaction term. Based on the common trend assumption, we use retail markets as the within-city counterfactual. City-specific market characteristics are removed by the difference-in-difference structure. For the global financial crisis (GFC), we use a sample from 2005 to 2009 with dummy variable D_{Crisis} equal to one for 2008 and 2009 as the aftermath of the global financial crisis. For the sovereign debt crisis, we use a sample from 2005 to 2011, with 2010 and 2011 defined as the turmoil period. For the dotcom bubble burst, we use a sample from 1995 to 2001, with turmoil dummies equal to one for 2000 and 2001. The estimation is based on OLS. Cluster-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Financial Crisis 2008-2009		Sovereign Debt Crisis 2010-2011		Dotcom Bubble Burst 2000-2001	
	Model I	Model II	Model I	Model II	Model I	Model II
constant	0.207*** (0.017)	0.249*** (0.040)	0.230*** (0.017)	0.238*** (0.041)	0.101*** (0.023)	0.129* (0.069)
D_{Crisis}	-0.279*** (0.039)	-0.279*** (0.039)	-0.097 (0.025)	-0.097*** (0.025)	-0.041 (0.029)	-0.048 (0.047)
D_{Office}	0.022 (0.026)	0.024 (0.025)	-0.022 (0.024)	-0.0022 (0.024)	-0.016 (0.027)	0.001 (0.042)
$D_{Crisis} \times D_{Office}$	-0.110** (0.051)	-0.111** (0.051)	0.023 (0.036)	0.023 (0.036)	-0.081** (0.039)	-0.098* (0.054)
Δ Exchange Rate	0.510*** (0.171)	0.494*** (0.171)	0.555*** (0.148)	0.552*** (0.149)	1.017*** (0.151)	1.112*** (0.229)
log(Floor Space)		-0.005 (0.004)		-0.001 (0.004)		-0.002 (0.006)
GFC Turmoil			-0.338*** (0.027)	-0.338*** (0.027)		
Observations	175	175	244	244	225	170
Adj.- R^2	0.584	0.583	0.537	0.535	0.237	0.222

Table 7: Difference-in-Difference Model: Financial versus Non-Financial Center

This table shows the regression result of the difference-in-difference model for office markets. We regress office market returns r_{it} on the dummy variables for the financial crisis period, D_{Crisis} , the financial center dummy, D_{Center} , and their interaction term. We use non-financial centers as counterfactual. We include a set of additional control variables in the model. For the global financial crisis (GFC), we use a sample from 2005 to 2009 with dummy variable D_{Crisis} equal to one for 2008 and 2009 as the aftermath of the global financial crisis. For the sovereign debt crisis, we use a sample from 2005 to 2011, with 2010 and 2011 defined as the turmoil period. For the dotcom bubble burst, we use a sample from 1995 to 2001, with turmoil dummies equal to one for 2000 and 2001. The estimation is based on OLS. Cluster-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Financial Crisis 2008-2009		Sovereign Debt Crisis 2010-2011		Dotcom Bubble Burst 2000-2001	
	Model I	Model II	Model I	Model II	Model I	Model II
constant	0.165*** (0.018)	-0.071 (0.094)	0.189*** (0.015)	-0.101 (0.087)	0.095*** (0.012)	0.171** (0.082)
D_{Crisis}	-0.243*** (0.032)	-0.161*** (0.031)	-0.074*** (0.017)	-0.026 (0.019)	-0.066*** (0.019)	-0.095*** (0.025)
D_{Center}	0.044 (0.027)	0.029 (0.023)	-0.008 (0.013)	-0.016 (0.013)	-0.003 (0.019)	-0.010 (0.028)
$D_{Crisis} \times D_{Center}$	-0.129** (0.051)	-0.105** (0.042)	-0.004 (0.025)	-0.002 (0.026)	-0.041 (0.030)	-0.038 (0.040)
Δ Exchange Rate	0.743*** (0.170)	-0.563 (0.756)	0.820*** (0.155)	-0.529 (0.499)	0.935*** (0.072)	1.079*** (0.115)
log(Floor Space)		0.019** (0.009)		-0.025*** (0.009)		-0.006 (0.009)
Δ Population		-1.062** (0.464)		-0.257 (0.283)		0.611 (0.441)
Term Spread		-0.279 (1.213)		-0.193 (0.541)		
Δ GDP Capita		0.749*** (0.268)		0.758*** (0.236)		
Δ REIT		0.312 (0.348)		0.336 (0.222)		
Δ Residential		0.317 (0.226)		0.189 (0.127)		
Δ Claims		0.211*** (0.065)		0.170*** (0.050)		
Δ Sentiment		-0.007*** (0.001)		-0.008*** (0.001)		
GFC Turmoil			-0.303*** (0.027)	-0.228*** (0.022)		
Observations	275	275	385	385	398	290
Adj.- R^2	0.593	0.656	0.531	0.623	0.322	0.408

Table 8: Effect of Financial Center-Specific SRISK on Office Market Returns

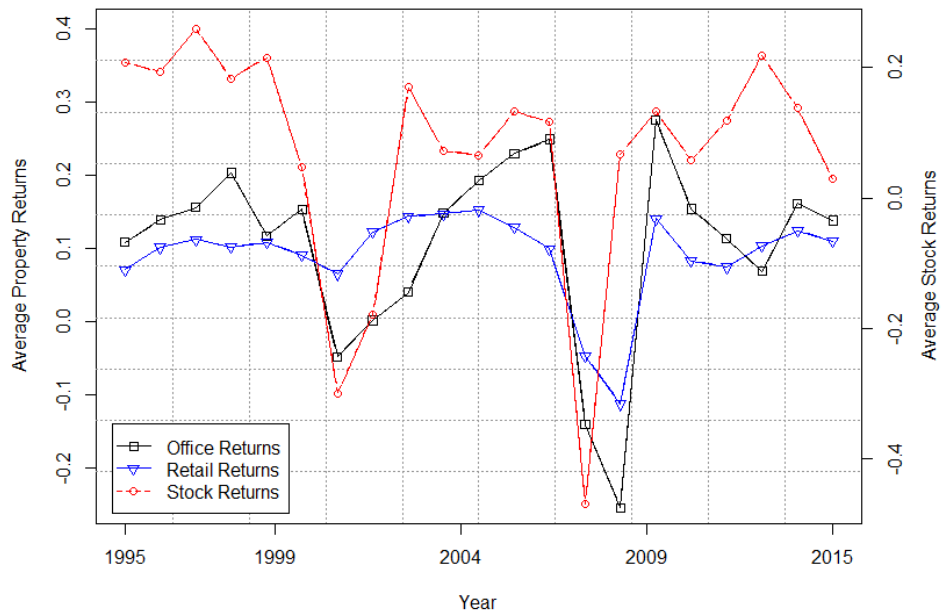
This table shows the effect of the total financial center-specific systemic risk on international office markets. Estimates are based on OLS. *SRISK high* and *SRISK low* capture office markets with the 25% highest and 25% lowest aggregated financial center-specific systemic risk per year. The *Financial Crisis* dummy is equal to one for the years 2008 and 2009. $\times SRISK_{high}$ and $\times SRISK_{low}$ define the interaction of both variables with the Financial Crisis-dummy, respectively. Cluster-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Model I	Model II	Model III	Model IV	Model V
Stock Returns	0.123*** (0.024)	0.121*** (0.024)	0.123*** (0.021)	0.124*** (0.021)	0.123*** (0.021)
log(SRISK)	-0.001 (0.001)				
Δ SRISK		-0.007 (0.004)			
Δ GDP Capita	0.840*** (0.197)	0.910*** (0.228)	0.843*** (0.179)	0.830*** (0.179)	0.844*** (0.180)
Term Spread	-0.633*** (0.220)	-0.578** (0.248)	-0.746*** (0.224)	-0.777*** (0.222)	-0.745*** (0.223)
Δ Floor Space	-0.739*** (0.216)	-0.809*** (0.257)	-0.780*** (0.208)	-0.762*** (0.217)	-0.780*** (0.208)
Δ Claims	0.068** (0.033)	0.084** (0.034)	0.076*** (0.028)	0.070** (0.028)	0.076*** (0.028)
Δ Sentiment	-0.007*** (0.0001)	-0.007*** (0.0002)	-0.007*** (0.0001)	-0.006*** (0.0003)	-0.007*** (0.0001)
Δ Exchange Rate	0.017 (0.269)	-0.047 (0.320)	-0.003 (0.237)	-0.011 (0.238)	-0.003 (0.239)
SRISK high			-0.005 (0.008)	0.007 (0.011)	-0.005 (0.008)
SRISK low			0.001 (0.009)	0.001 (0.009)	0.001 (0.010)
Financial Crisis	-0.143*** (0.019)	-0.137*** (0.018)	-0.139*** (0.017)	-0.119*** (0.015)	-0.139*** (0.020)
$\times SRISK_{high}$				-0.090** (0.045)	
$\times SRISK_{low}$					-0.002 (0.031)
Observations	830	787	946	946	946
Adj.- R^2	0.509	0.517	0.509	0.514	0.508

Figure 1: Performance of Commercial Real Estate and Stock Market Returns

This figure illustrates the performance of the commercial real estate (office and retail) and stock market returns from 1995 to 2015. We compute cross-sectional average returns for the United States, Europe, and Asia-Pacific. Returns are measured in decimals.

Panel A: Commercial Real Estate and Stock Market Returns in USA



Panel B: Commercial Real Estate and Stock Market Returns in Europe

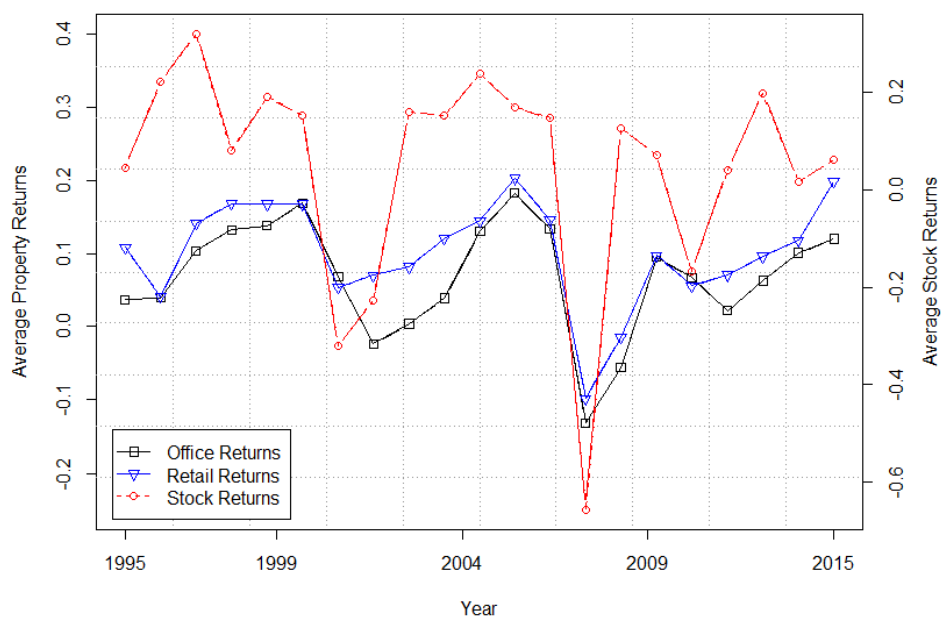


Figure 1 continued.

Panel C: Commercial Real Estate and Stock Market Returns in Asia-Pacific

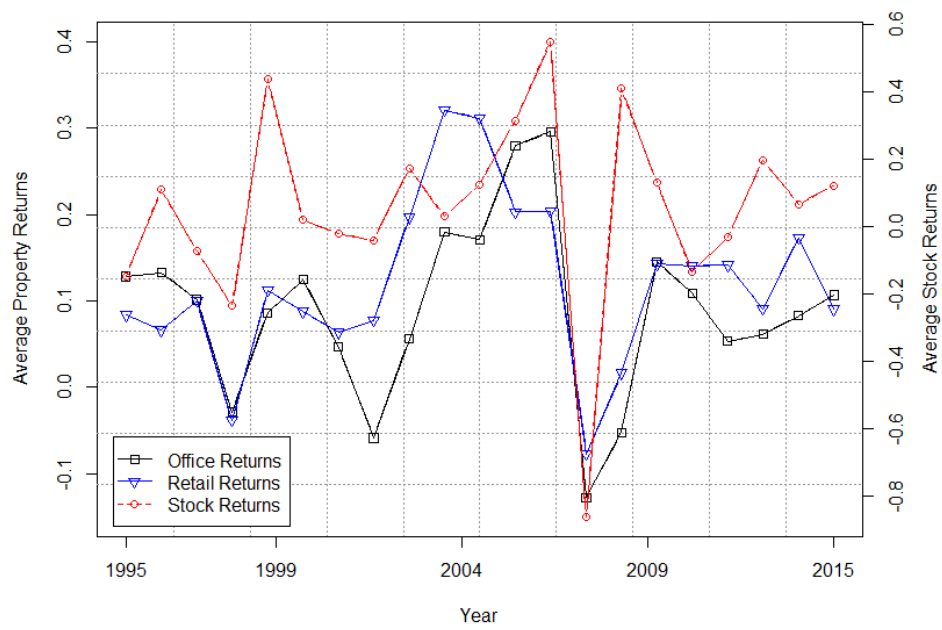


Figure 2: Impulse Response Function

This figure illustrates the impulse response functions of a positive shock of stock returns (top) and office returns (bottom) on stock returns and office returns, respectively. The GMM system is estimated using the forward-orthogonal transformation (Arellano and Bover (1995)). A two-way fixed effects specification resembles a common factor representation to account for the cross-sectional dependence across the endogenous variables (Sarafidis and Wansbeek (2012)). The impulse response functions are orthogonalized based on the Cholesky decomposition of the covariance matrix. The Hannan-Quinn (HQ) and Bayesian information criteria suggest an optimal lag length of order one. The confidence intervals are based on 200 Monte Carlo simulations.

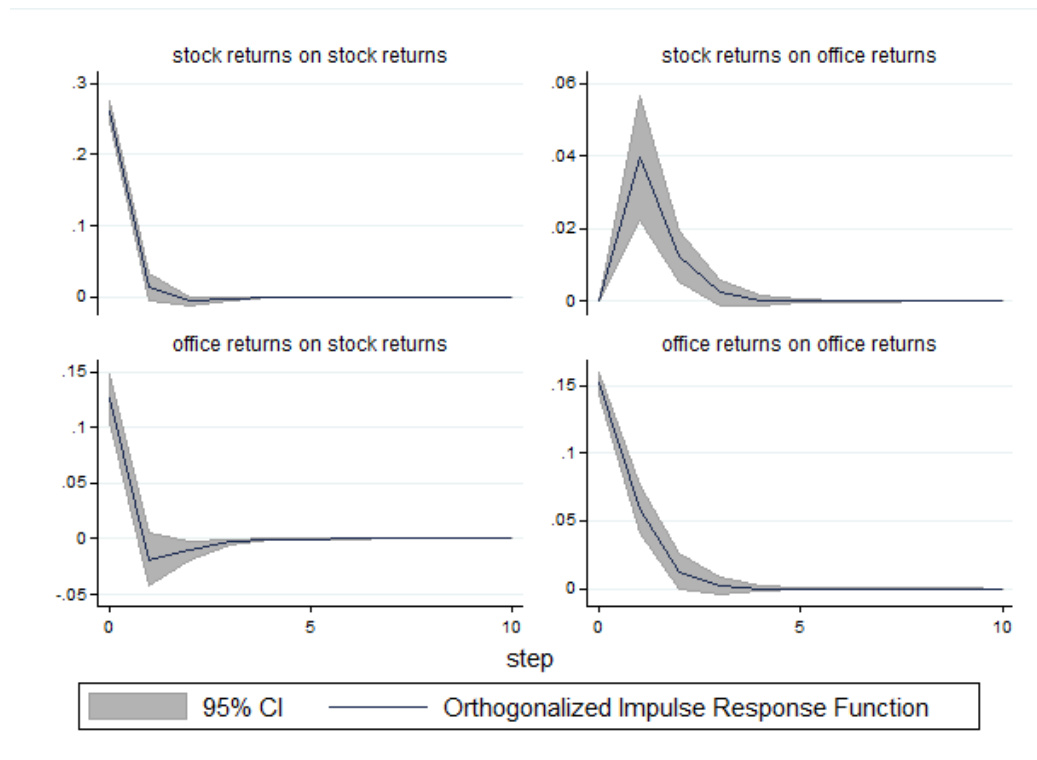


Figure 3: Financial Institutions in International Financial Centers

This figure illustrates the distribution of domestic and foreign main office locations of financial institutions across international financial centers. We include only financial institutions with main offices in at least two financial centers.

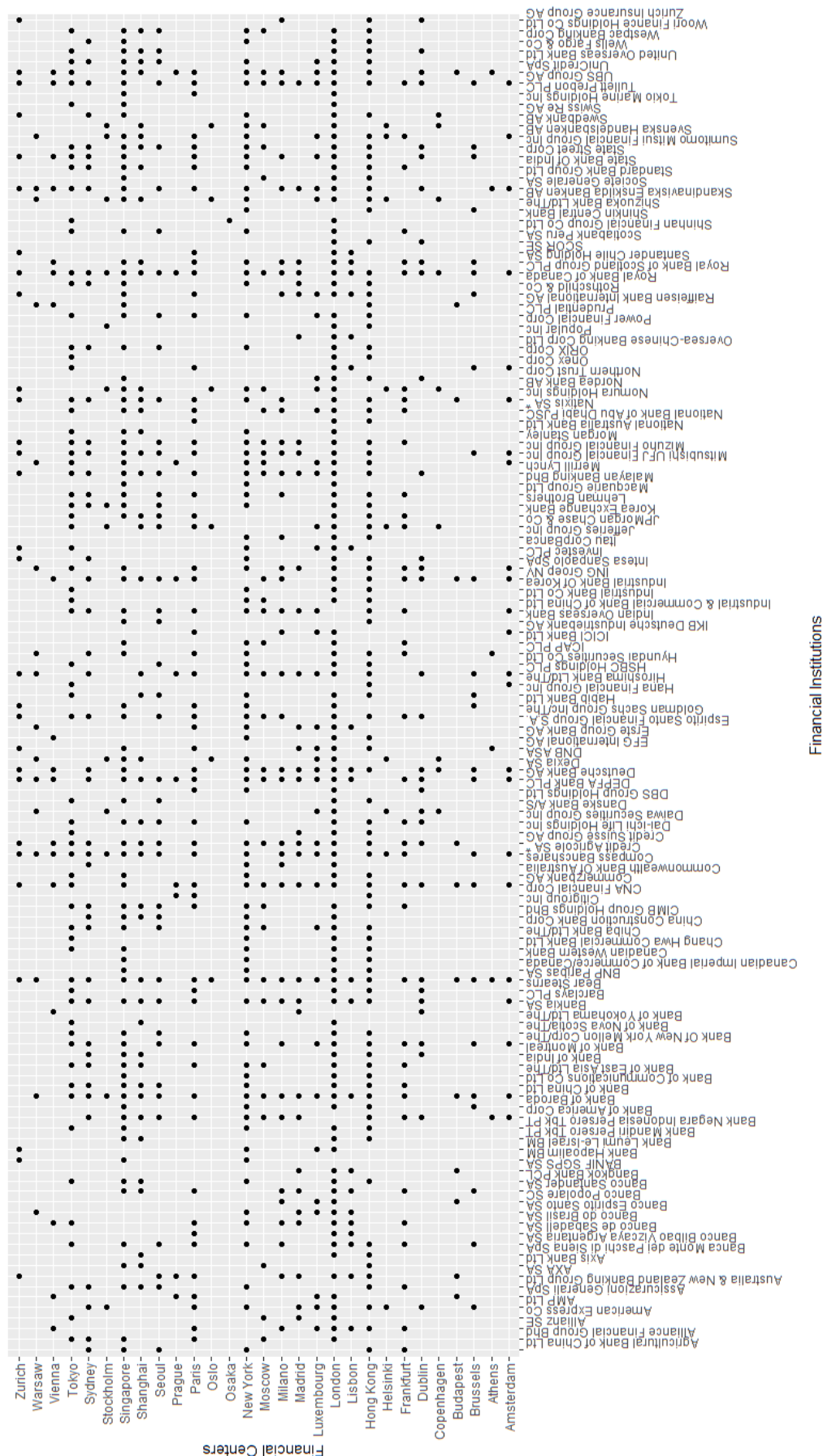
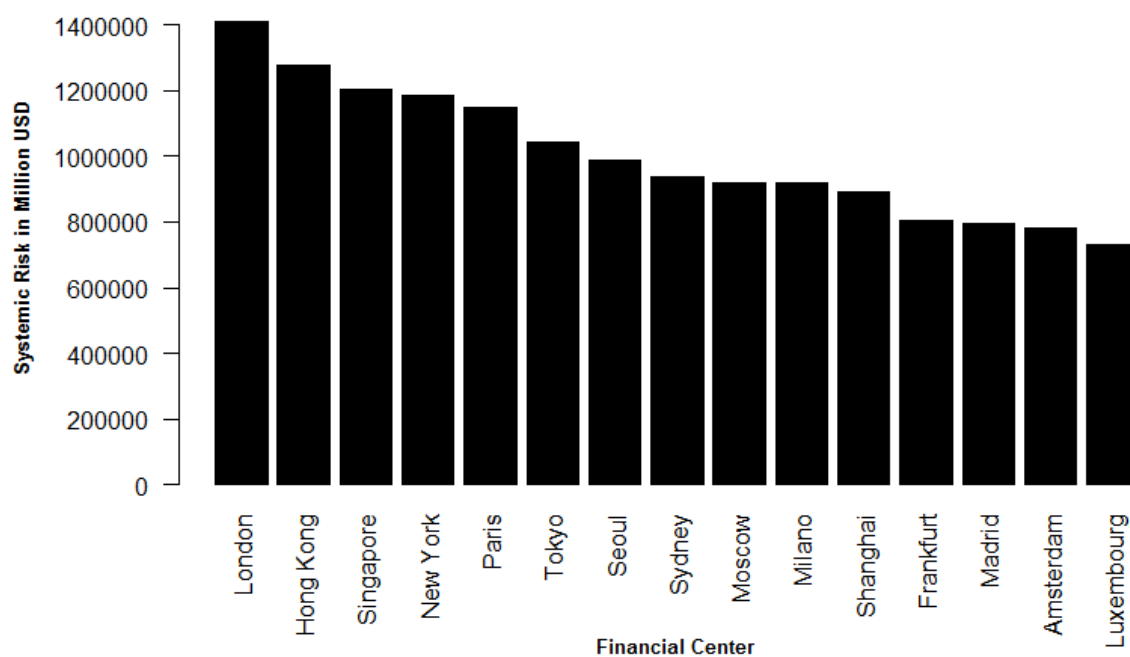


Figure 4: SRISK Ranking of Financial Centers

This figure shows the cross-sectional and time-series variation of the financial center-specific systemic risk exposure. Panel A ranks the 15 financial centers with the highest systemic risk exposure. Panel B shows the time-variation of the average systemic risk exposure of all financial centers.

Panel A: SRISK Ranking of Financial Centers



Panel B: Average SRISK Exposure of Office Markets over Time

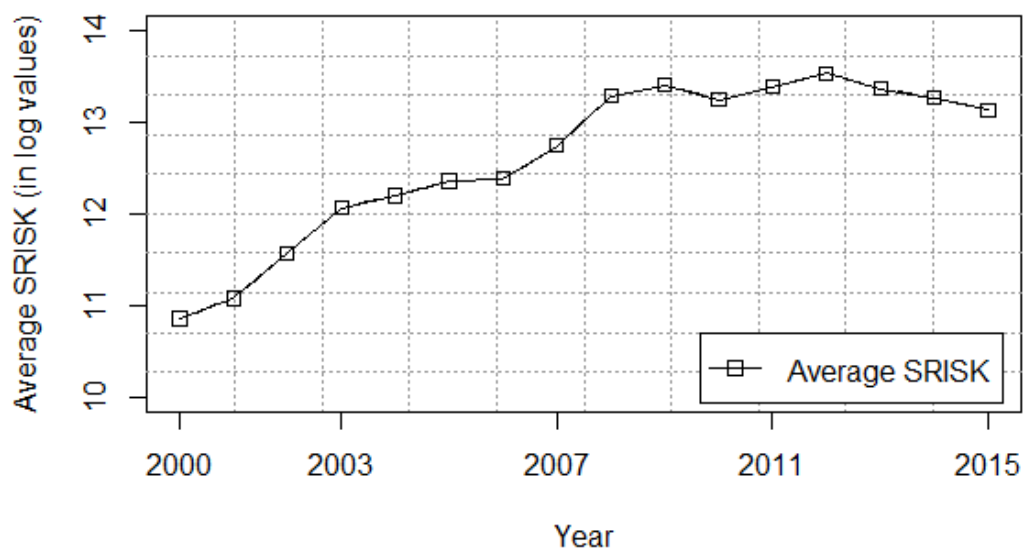


Figure 5: Average SRISK in Financial Centers versus Non-Financial Centers

This figure illustrates the mean difference between office markets in financial centers and non-financial centers during the sample period from 2000 to 2015. Financial centers include all cities in our sample that host the national stock exchange trading platform. We exclude Boston, Chicago, San Francisco, and Washington from the sample. Based on our definition they would be classified as non-financial centers, while they are ranked as top financial centers by the Global Financial Center Index (GFCI) and the Xinhua/Dow Jones International Financial Centers Development Index.

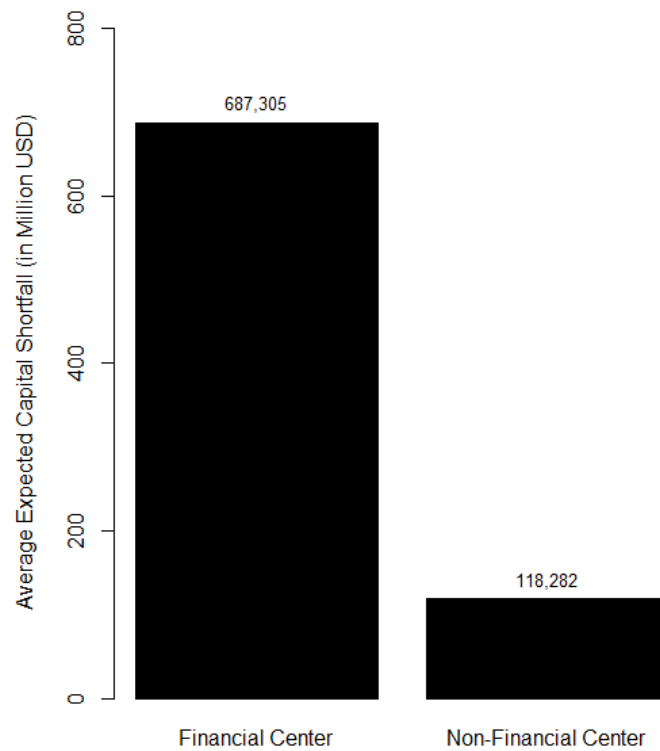
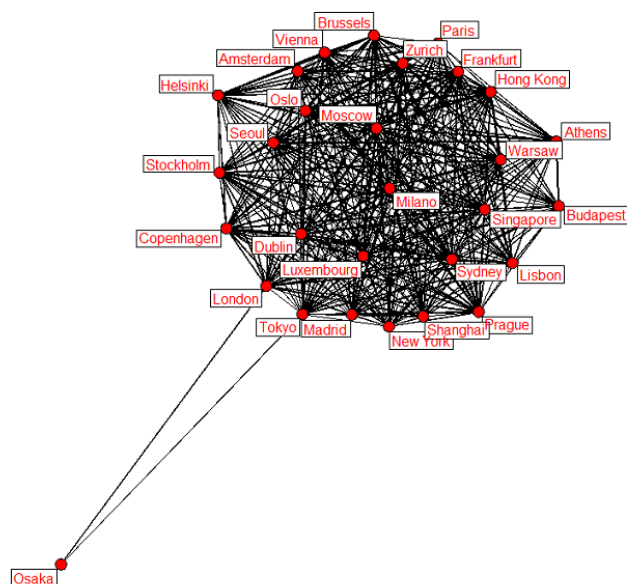


Figure 6: Interconnectedness of Financial and Non-Financial Centers

Panels A and B of the figure illustrate the linkage among financial and non-financial centers as implied by the corresponding weighting matrices. We show the interconnectedness representative for the year 2007.

Panel A: Financial Centers



Panel B: Non-Financial Centers

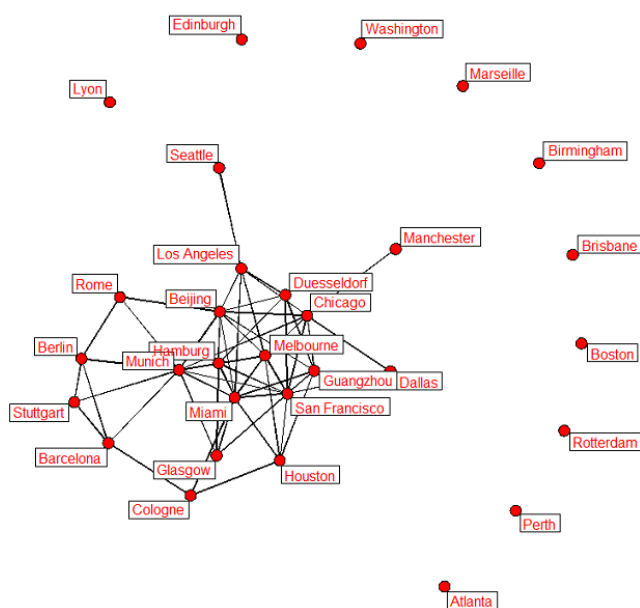


Table A.1: Return Comparison: PMA versus NCREIF for the U.S

This table compares total market returns from Property Market Analysis (PMA) with annualized quarterly total property index returns from the National Council of Real Estate Investment Fiduciaries (NCREIF) for the USA from 2000 to 2015. This sample restriction is in line with the data availability of the SRISK measure and corresponds to the sample we use in the analysis. Annualized returns are based on the average quarter return for each year and are available for Metropolitan Statistical Areas (MSAs). Panel A shows the summary statistics of both datasets for the office and the retail sector, respectively. Panel B shows the estimated coefficients of the time lags based on a panel fixed effects model with macroeconomic fundamentals. Standard errors are robust based on the Arellano and Bond (1991) two-step GMM approach. We also report the corresponding Sargan test of overidentifying restrictions (valid under the null hypothesis) and the test for first- and second-order zero autocorrelation in first-differenced residuals (whereas the first-differenced errors are only allowed to be first-order serially correlated). Panel C illustrates the correlation between PMA and the corresponding NCREIF returns for U.S. cities in our sample. For each MSA, we provide information about the average, the minimum and the maximum number of quarterly self-reported properties (Min.Prop. and Max.Prop) used for the NCREIF index construction.

Panel A: Summary Statistics of PMA versus NCREIF NPI Returns					
	Mean	Std.Dev.	Min.	Max.	Obs.
Office					
PMA	0.08	0.17	-0.52	0.49	165
NCREIF NPI	0.08	0.11	-0.31	0.35	165
Retail					
PMA	0.09	0.08	-0.17	0.21	150
NCREIF NPI	0.11	0.09	-0.17	0.34	162
Panel B: Autocorrelation of PMA and NCREIF NPI Returns					
	Time Lag	Sargan Test	AR(1)	AR(2)	Obs.
PMA	-0.021 (0.093)	17.959	-2.909***	-1.544	315
NCREIF NPI	-0.032 (0.077)	19.795	-2.408**	-1.491	315
Panel C: Correlation between PMA and NCREIF NPI Returns					
	Correlation	Sector	Avg.Prop.	Min.Prop.	Max.Prop.
Atlanta	0.814	office	48.16	37	71
Boston	0.879	office	20.07	11	48
Chicago	0.711	office	58.38	43	76
Dallas	0.730	office	52.70	41	63
Houston	0.719	office	30.80	24	41
Los Angeles	0.945	office	64.40	30	91
Miami	0.755	office	20.68	13	36
New York	0.933	office	52.10	30	80
San Francisco	0.777	office	47.85	32	79
Seattle	0.889	office	50.63	22	75
Washington	0.810	office	128.20	70	162
Atlanta	0.806	retail	40.76	18	58
Boston	0.748	retail	10.67	5	25
Chicago	0.845	retail	53.13	23	75
Dallas	0.833	retail	25.21	12	37
Houston	0.828	retail	20.25	11	35
Los Angeles	0.908	retail	31.82	15	61
Miami	0.739	retail	14.78	5	27
New York	0.836	retail	18.61	6	46
San Francisco	0.802	retail	9.97	6	15
Washington	0.889	retail	45.57	16	70

Table A.2: Commercial Real Estate Market Coverage

This table contains the market coverage of our sample. We show the data availability for commercial real estate office and retail markets for each city in our sample. In Panel A, we list all available markets in financial centers with a stock exchange. We also show the corresponding trading platform and the national stock market index that is used in our sample. In Panel B, we list all available commercial real estate office and retail markets of all non-financial centers in our sample.

Panel A: Financial Centers					
City	Country	Office	Retail	Trading Platform	Stock Index
Amsterdam	Netherlands	Yes	Yes	Euronext	AEX
Athens	Greece	Yes	No	Athen Stock Exchange	ATHEX Composite
Brussels	Belgium	Yes	Yes	Euronext	Bel20
Budapest	Hungary	Yes	Yes	Budapest Stock Exchange	BUX
Copenhagen	Denmark	Yes	Yes	OMX Nordic Exchange	OMXC20
Dublin	Ireland	Yes	Yes	Irish Stock Exchange	ISEQ
Frankfurt	Germany	Yes	Yes	Deutsche Börse	DAX30
Helsinki	Finland	Yes	No	OMX Nordic Exchange	OMXH25
Hong Kong	Hong Kong	Yes	Yes	Hong Kong Stock Exchange	Hang Seng Index
Lisbon	Portugal	Yes	Yes	Euronext	PSI20
London	United Kingdom	Yes	Yes	London Stock Exchange	FTSE100
Luxembourg	Luxembourg	Yes	No	Luxembourg Stock Exchange	LUX SE General
Madrid	Spain	Yes	Yes	BME Spanish Exchange	IBEX35
Milan	Italy	Yes	Yes	Borsa Italia	FTSE MIB
Moscow	Russia	Yes	No	Moscow Exchange	MICEX Index
New York	USA	Yes	Yes	New York Stock Exchange	SNP500
Osaka	Japan	Yes	Yes	Japan Exchange Group	NIKKEI Futures
Oslo	Norway	Yes	No	Oslo Bors	OBX
Paris	France	Yes	Yes	Euronext	CAC40
Prague	Czech Republic	Yes	Yes	Prague Stock Exchange	PX50
Seoul	South Korea	Yes	Yes	Korea Exchange	KOSPI
Shanghai	China	Yes	Yes	Shanghai Stock Exchange	SE A SPI
Singapore	Singapore	Yes	Yes	Singapore Exchange	Straits Time Index
Stockholm	Sweden	Yes	Yes	OMX Nordic Exchange	OMXS30
Sydney	Australia	Yes	Yes	Australian Sec. Exchange	ASX
Tokyo	Japan	Yes	Yes	Japan Exchange Group	NIKKEI25
Vienna	Austria	Yes	Yes	Wiener Börse	ATX
Warsaw	Poland	Yes	Yes	Warsaw Stock Exchange	WIG
Zurich	Switzerland	Yes	No	SIX Swiss Exchange	SSMI

Table A.2 continued.

Panel B: Non-financial Centers			
City	Country	Office	Retail
Atlanta	USA	Yes	Yes
Barcelona	Spain	Yes	Yes
Beijing	China	Yes	Yes
Berlin	Germany	Yes	Yes
Birmingham	United Kingdom	Yes	Yes
Boston	USA	Yes	Yes
Brisbane	Australia	Yes	No
Chicago	USA	Yes	Yes
Cologne	Germany	Yes	Yes
Dallas	USA	Yes	Yes
Dusseldorf	Germany	Yes	No
Edinburgh	United Kingdom	Yes	No
Glasgow	United Kingdom	Yes	Yes
Guangzhou	China	Yes	Yes
Hamburg	Germany	Yes	Yes
Houston	USA	Yes	Yes
Lille	France	Yes	Yes
Los Angeles	USA	Yes	Yes
Lyon	France	Yes	Yes
Manchester	United Kingdom	Yes	Yes
Marseille	France	Yes	Yes
Melbourne	Australia	Yes	Yes
Miami	USA	Yes	Yes
Munich	Germany	Yes	Yes
Nagoya	Japan	Yes	No
Perth	Australia	Yes	No
Rome	Italy	Yes	Yes
Rotterdam	Netherlands	Yes	No
San Francisco	USA	Yes	Yes
Seattle	USA	Yes	No
Stuttgart	Germany	Yes	Yes
Washington	USA	Yes	Yes

Table A.3: List of Financial Institution with highest SRISK

This table contains a ranking of the 40 financial institutions with the highest SRISK, denominated in million USD, that is observed in any month during the sample period from 2000 to 2015. The SRISK measure is calculated as the expected capital shortfall given a 40% decline in the MSCI world equity index over the next 6 months. The data are provided by the NYU Stern Volatility Lab.

Institution	SRISK	Month	Year	Headquarter	Country
Royal Bank of Scotland Group PLC	186,877	11	2008	Edinburgh	United Kingdom
Mitsubishi UFJ Financial Group Inc	177,001	1	2012	Tokyo	Japan
Deutsche Bank AG	170,167	3	2008	Frankfurt	Germany
Barclays PLC	157,427	1	2009	London	United Kingdom
Bank of America Corp	154,312	4	2009	Charlotte, NC	USA
Citigroup Inc	141,770	2	2009	New York	USA
BNP Paribas SA	140,504	1	2009	Paris	France
Mizuho Financial Group Inc	140,389	11	2012	Tokyo	Japan
JPMorgan Chase & Co	126,504	2	2009	New York	USA
Credit Agricole SA	126,388	11	2012	Montrouge	France
Sumitomo Mitsui Financial Group Inc	107,646	11	2012	Tokyo	Japan
HSBC Holdings PLC	99,166	3	2009	London	United Kingdom
ING Groep NV	94,726	1	2009	Amsterdam	Netherlands
Bank of China Ltd	91,706	8	2013	Beijing	China
UBS Group AG	90,748	5	2008	Basel	Switzerland
China Construction Bank Corp	86,169	6	2013	Beijing	China
Societe Generale SA	84,762	1	2012	Paris	France
Lloyds Banking Group PLC	77,239	6	2009	London	United Kingdom
Agricultural Bank of China Ltd	75,497	7	2013	Beijing	China
Wells Fargo & Co	75,119	2	2009	San Francisco	USA
American International Group Inc	74,333	9	2008	New York	USA
UniCredit SpA	70,577	11	2008	Milano	Italy
Commerzbank AG	70,531	3	2009	Frankfurt	Germany
HBOS PLC	70,123	9	2008	Edinburgh	United Kingdom
Morgan Stanley	69,571	9	2008	New York	USA
Freddie Mac	68,939	8	2008	Tysons Corner	USA
Fannie Mae	66,701	8	2008	Washington	USA
Banco Santander SA	66,636	5	2012	Madrid	Spain
Merrill Lynch	66,088	3	2008	New York	USA
Goldman Sachs Group Inc	62,491	10	2008	New York	USA
Ind. & Commercial Bank of China Ltd	59,517	12	2013	Beijing	China
Lehman Brothers	57,692	3	2008	New York	USA
Wachovia Bank	55,795	9	2008	Charlotte, NY	USA
Allianz SE	55,310	2	2009	Munich	Germany
Credit Suisse Group AG	51,613	1	2012	Zurich	Switzerland
Dexia SA	48,036	7	2008	Brussels	Belgium
MetLife Inc	47,263	11	2012	New York	USA
London Stock Exchange Group PLC	46,337	12	2013	London	United Kingdom
AXA SA	42,536	12	2011	Paris	France

Table A.4: Definition of Control Variables

Variables	Description	Source
Stock Returns	We compute annual log-returns of stock market indices representing the corresponding stock exchange trading platform in each country.	Thomson Reuters Datastream
log(SRISK)	This variable (in logs) equals the city-specific sum of the positive expected capital shortfall of all institutions with located main offices in a city. We compute the average value each year.	NYU Stern V-Lab, Own Calculation
Δ GDP Capita	We compute log-differences of national GDP per capita. GDP is measured in constant prices. For China, GDP is measured in current prices.	Thomson Reuters Datastream
Term Spread	Term spread is computed as difference between 10-year government bond yields and the three-month interbank rate. Due to data restrictions, we use six-month interest rates instead of long-term interest rates for China, the Czech Republic, Greece, Hungary, and Poland.	Thomson Reuters Datastream, Own Calculation
Δ Floor Space	City-level construction of commercial real estate for each sector (office, retail) reflects changes (computed as log-differences) in the stock supply.	Property Market Analysis (PMA)
Δ REIT	We compute returns on the NAREIT/MSCI REIT. For Finland and Ireland we use data from FTSE EPRA REIT. Missing values for Hungary, South Korea, and Poland are replaced by forecasts.	Thomson Reuters Datastream
Δ Population	We compute population growth at the city-level as log-differences from levels. Missing values within sample are replaced by fitted values from a geometric interpolation.	Quandl, Various Sources
Δ Residential	We compute log-returns of the residential housing market for each country.	Bank for International Settlements (BIS)
Correlation to MSCI	This variable equals the yearly correlation (based on daily data) between stock market returns and the global MSCI world index returns.	Thomson Reuters Datastream, Own Calculation
Δ Claims	We include international cross-border claims (dollar-denominated) on each country to proxy capital inflow. The variable captures the change in global amounts outstanding from the national non-bank sector (bank loans, deposits, and other instruments, e.g., debt securities).	Bank for International Settlement (BIS)
Δ Sentiment	Investor sentiment is computed as log-differences of the OECD Consumer sentiment. For Hong Kong, we use the Public Sentiment Index (PSI). For Singapore, we use Business Expectations for the Service Sector, providing a business outlook for the next six months.	OECD, Various Sources

Table A.4 continued.

Control Variables		
CMBS Spread	We compute the U.S. CMBS yield spread relative to the U.S. 10-year government bond. This Barclays Capital bond index reflects the performance of investment-grade CMBSs in the U.S.	Thomson Reuters Datastream
TED Spread	For the U.S. and Asia-Pacific, we compute the difference between the annualized three-month LIBOR rate and the annualized three-month U.S. Treasury Bill rate as the TED spread. For the European area, we use the difference between the annualized three-month EURIBOR and the annualized three-month EONIA rate.	Thomson Reuters Datastream
Crisis Dummy	This dummy equals 1 for the crisis periods 2001/2002 (dotcom crisis), 2007/2008 (global financial crisis), 2010/2011 (sovereign debt crisis), and 0, otherwise.	Own Computation
Δ Exchange Rate	We compute log-changes of nominal exchange rates for all countries relative to the U.S. dollar.	Thomson Reuters Datastream

Table A.5: Summary Statistics of Explanatory Variables

This table contains the descriptive summary of the explanatory variables used in our sample. Each variable is pooled over the cross-section (either city-level, country-level, global-level) from 2000 to 2015. This sample restriction is in line with the data availability of the SRISK measure and corresponds to the sample we use in the analysis. Representative trading platforms are located in 29 cities. Returns and growth rates (indicated by Δ) are calculated as log-differences. All values are measured in decimals.

City-Level	Mean	Std.Dev.	Min.	Max.	Obs.
log(SRISK.total)	11.63	2.23	3.04	14.83	870
Δ Floor Space Office	0.03	0.04	-0.04	0.42	973
Δ Floor Space Retail	0.03	0.05	-0.02	0.68	768
Stock Returns	0.03	0.27	-1.24	1.17	976
Correlation	0.51	0.24	-0.12	0.93	464
Δ Population	0.01	0.03	-0.66	0.18	972
Country-Level	Mean	Std.Dev.	Min.	Max.	Obs.
Δ GDP capita	0.04	0.10	-0.26	0.41	448
Term Spread	0.01	0.02	-0.07	0.22	448
Δ REITs	0.00	0.05	-0.29	0.13	448
Δ Residential	0.04	0.07	-0.23	0.39	448
Δ Exchange Rate	0.00	0.09	-0.46	0.19	448
Δ Claims	0.08	0.18	-0.49	0.67	448
Δ Sentiment	-0.05	2.55	-0.53	0.24	448
Global Level	Mean	Std.Dev.	Min.	Max.	Obs.
MSCI World Returns	0.03	0.24	-0.63	0.38	16
U.S. CMBS Spread	0.00	0.39	-0.70	1.05	16
TED Spread	0.02	0.02	0.00	0.06	16

Table A.6: Correlation Structure of Explanatory Variables

This table shows the Pravais-Pearson correlation matrix of the explanatory variables.

	log(SRISK.total)	ΔGDP Capita	Stock Returns	Term Spread	ΔFloor Space	ΔREITs	ΔPopulation	ΔResidential	ΔClaims	ΔSentiment	Correlation	ΔExchange Rate	MSCI World Returns	U.S. CMBS Spread	TED Spread
log(SRISK.total)	1.000														
ΔGDP Capita	-0.083	1.000													
Stock Returns	0.003	-0.015	1.000												
Term Spread	0.047	-0.203	-0.020	1.000											
ΔFloor Space	-0.177	0.319	0.003	-0.323	1.000										
ΔREITs	0.023	0.496	-0.109	-0.025	0.067	1.000									
ΔPopulation	0.081	0.222	0.050	-0.136	0.305	-0.025	1.000								
ΔResidential	-0.106	0.322	0.095	-0.357	0.257	0.088	0.150	1.000							
ΔClaims	-0.150	0.402	0.220	-0.228	0.189	0.140	0.073	0.338	1.000						
ΔSentiment	-0.018	-0.020	-0.025	-0.009	0.015	-0.012	0.001	-0.086	-0.056	1.000					
Correlation	0.306	-0.188	-0.134	0.130	-0.367	-0.025	-0.044	-0.080	-0.177	-0.003	1.000				
ΔExchange Rate	-0.027	0.781	-0.112	-0.010	0.023	0.656	0.025	0.121	0.307	-0.001	-0.024	1.000			
MSCI World Returns	0.011	0.233	0.095	0.028	-0.099	-0.016	-0.001	0.171	0.028	-0.070	-0.015	0.100	1.000		
U.S. CMBS Spread	0.095	0.044	-0.172	0.100	-0.100	0.030	0.009	-0.076	-0.136	-0.053	0.125	0.047	0.314	1.000	
TED Spread	0.106	-0.078	-0.252	-0.018	-0.089	-0.061	-0.011	-0.172	-0.111	-0.014	-0.148	0.011	-0.345	-0.011	1.000

Table A.7: Exposure to Systematic Banking Market Risk

This table shows the relationship between the aggregated expected capital shortfall (measured in log-values) as endogenous variable and systematic risk factors of local banking markets as explanatory variables. The sample ranges from 2000 to 2015. Estimates are based on OLS. We use systematic risk factors related to credit risk and interest rate risk. The *U.S. CMBS Spread* is the difference between the yield on U.S. CMBS index and the long-term government bond. The *TED Spread* is defined as the difference between the annualized three-month LIBOR rate and the corresponding three-month U.S. Treasury Bill rate. For the European area, we use the difference between the three-month EURIBOR and the three-month EONIA rate. Δ *MSCI World* measures the global stock market performance. The *Term Spread* reflects the difference between long-term government bond yields and short-term interbank rates as a local risk factor. *Long-Term Interest* reflects the local interest rate risk. We use the U.S. long-term government bond yield (*U.S. Long-Term Interest*) and the U.S. 3-month Treasury Bill rate (*U.S. Short-Term Interest*) as proxies for global interest rate risk. Cluster-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Model I	Model II	Model III	Model IV
U.S. CMBS Spread	0.198** (0.081)	0.185** (0.093)	-0.071 (0.077)	-0.049 (0.079)
TED Spread	-12.084 (14.156)	-12.589 (14.143)	-8.050 (14.433)	-12.169 (14.229)
Δ MSCI World	-0.281 (0.280)	-0.307 (0.282)	-0.205 (0.285)	0.036 (0.288)
Term Spread	-5.160 (0.215)			
Long-Term Interest		-10.119 (9.183)		
U.S. Long-Term Interest			-52.424*** (8.978)	
U.S. Short-Term Interest				-21.460*** (3.544)
Observations	849	849	854	854
Adj.- R^2	0.002	0.010	0.060	0.036

Table A.8: Correlated Risk: Upper versus Lower Tercile of Average SRISK

This table replicates the results of Model III from Tables 2 and 3 when we use cities with the upper and lower tercile of the average SRISK level from 2000 to 2015 as financial and non-financial centers. *Turmoil* periods are the financial crisis period 2007/2008. To measure spatial dependence during turmoil periods, the elements of the weighting matrix are restricted to zero for *normal* times. To measure dependence during normal times, we restrict the weighting matrix to zero for crisis periods. The Pesaran (2004) CD test shows *t*-statistics of the null hypothesis of residual independence. Spatial HAC-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Financial Centers (Upper Tercile)				Non-Financial Centers (Lower Tercile)			
	Office		Retail		Office		Retail	
	Turmoil	Normal	Turmoil	Normal	Turmoil	Normal	Turmoil	Normal
Spatial Lag	0.332*	0.236	0.085	-0.060	0.052	0.037	0.126	-0.019
	(0.193)	(0.212)	(0.173)	(0.163)	(0.191)	(0.093)	(0.206)	(0.104)
Stock Return	0.084	0.080	0.075	0.074	0.133*	0.137*	0.149*	0.142
	(0.058)	(0.056)	(0.057)	(0.056)	(0.078)	(0.081)	(0.088)	(0.087)
log(SRISK)	-0.028**	-0.027**	-0.011	-0.011	-0.003	-0.003	0.003	0.003
	(0.013)	(0.012)	(0.013)	(0.013)	(0.002)	(0.002)	(0.002)	(0.002)
Δ GDP Capita	0.520***	0.571***	0.596***	0.597***	0.884***	0.889***	0.045	0.041
	(0.190)	(0.184)	(0.203)	(0.204)	(0.211)	(0.212)	(0.222)	(0.223)
Term Spread	-0.086	-0.493	1.316	1.285	-0.754	-0.831	1.380**	1.290**
	(0.956)	(0.903)	(0.807)	(0.794)	(0.716)	(0.642)	(0.588)	(0.568)
Δ Floor Space	-1.083**	-1.127***	0.124	0.122	-1.642***	-1.634***	0.157	0.168
	(0.428)	(0.409)	(0.184)	(0.184)	(0.453)	(0.446)	(0.253)	(0.268)
Δ REIT	0.044	-0.076	0.091	0.112	0.769**	0.749*	0.997***	1.070***
	(0.355)	(0.352)	(0.387)	(0.388)	(0.377)	(0.386)	(0.344)	(0.333)
Δ Population	1.810	1.857	0.387	0.417	0.341	0.374	0.442	0.503
	(1.204)	(1.212)	(0.854)	(0.853)	(0.968)	(0.961)	(0.859)	(0.852)
Δ Residential	0.601***	0.561***	0.508***	0.505***	-0.094	-0.094	0.412***	0.407***
	(0.192)	(0.193)	(0.147)	(0.146)	(0.115)	(0.112)	(0.105)	(0.102)
Δ Claims	-0.030	0.010	-0.012	-0.011	0.141***	0.142***	0.143*	0.145*
	(0.062)	(0.064)	(0.081)	(0.081)	(0.054)	(0.054)	(0.080)	(0.080)
Δ Sentiment	-0.006***	-0.006***	0.001	0.001	0.100	0.091	-0.349	-0.259
	(0.002)	(0.002)	(0.001)	(0.001)	(0.722)	(0.721)	(0.830)	(0.821)
Correlation to MSCI	0.141	0.138	0.109	0.106				
	(0.086)	(0.087)	(0.080)	(0.080)				
U.S. CMBS Spread	0.084***	0.060**	0.024	0.025	0.019	0.017	-0.0001	-0.0001
	(0.021)	(0.027)	(0.017)	(0.018)	(0.015)	(0.015)	(0.012)	(0.012)
TED Spread	-3.622***	-2.672***	0.096	0.089	-2.662***	-2.563***	-1.153*	-1.152*
	(0.954)	(0.994)	(1.008)	(1.022)	(0.662)	(0.650)	(0.659)	(0.684)
$\Delta \overline{GDP}$	0.322	-0.139	0.508*	0.573*	0.597**	0.559*	0.917***	0.948***
	(0.294)	(0.417)	(0.281)	(0.320)	(0.269)	(0.293)	(0.238)	(0.252)
$\Delta \overline{StockReturns}$	0.049	0.165**	0.118	0.140**	0.068	0.074	-0.012	0.010
	(0.092)	(0.075)	(0.077)	(0.065)	(0.100)	(0.088)	(0.087)	(0.086)
Crisis Dummy	-0.030	0.030	-0.038	-0.036	0.048*	0.051**	0.007	0.013
	(0.031)	(0.025)	(0.025)	(0.026)	(0.027)	(0.022)	(0.024)	(0.021)
Δ Exchange Rate	0.120	0.317	-0.168	-0.210	-1.564***	-1.533**	-1.473***	-1.588***
	(0.598)	(0.585)	(0.617)	(0.618)	(0.587)	(0.598)	(0.563)	(0.540)
Observations	320	320	272	272	320	320	256	256
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pesaran CD	1.81*	2.24***	1.53	1.96*	1.93	1.74*	2.27**	2.54**
Adj.- R^2	0.526	0.524	0.480	0.480	0.573	0.574	0.511	0.512

Table A.9: Correlated Risk Conditional on Global Property Market Portfolio

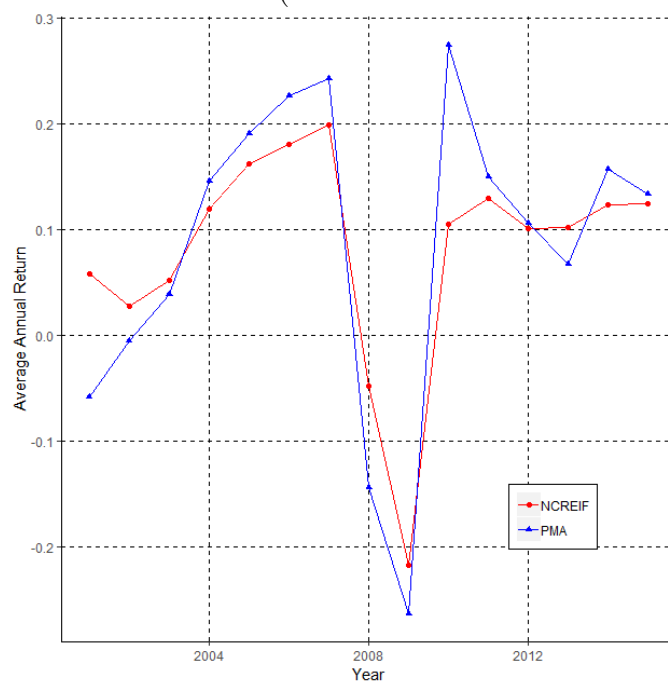
This table replicates Model III from Table 2. As endogenous variable we use residuals from a pooled panel model where office and retail market returns are separately regressed on the intercept and the corresponding equally-weighted global property market portfolio (with estimated exposure of 1.150 and 1.175 for the office and retail sector, respectively). *Turmoil* periods are the financial crisis period 2007/2008. To measure spatial dependence during turmoil periods, the elements of the weighting matrix are restricted to zero for *normal* times. To measure dependence during normal times, the weights are restricted to zero for crisis periods. The Pesaran (2004) CD test shows *t*-statistics of the null hypothesis of residual independence. Spatial HAC-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Office		Retail	
	Turmoil	Normal	Turmoil	Normal
Spatial Lag	0.296*** (0.084)	-0.479 (1.166)	0.028 (0.095)	0.007 (0.207)
Stock Returns	0.095* (0.053)	0.110 (0.075)	0.072 (0.054)	0.075 (0.054)
log(SRISK)	-0.023* (0.012)	-0.020 (0.019)	-0.010 (0.012)	-0.009 (0.014)
Δ GDP Capita	0.622*** (0.218)	0.821*** (0.265)	0.955*** (0.236)	0.955*** (0.237)
Term Spread	0.345 (0.595)	0.144 (1.068)	1.322** (0.635)	1.252* (0.754)
Δ Floor Space	-1.076*** (0.323)	-1.337*** (0.371)	0.015 (0.200)	0.003 (0.200)
Δ REIT	0.743** (0.289)	1.377 (1.034)	0.081 (0.371)	0.083 (0.379)
Δ Population	0.126 (0.177)	0.147 (0.225)	1.701* (0.974)	1.655* (0.978)
Δ Residential	0.702*** (0.179)	0.809*** (0.245)	0.549*** (0.137)	0.544*** (0.141)
Correlation to MSCI	0.072 (0.078)	0.087 (0.101)	0.026 (0.073)	0.027 (0.073)
Δ Claims	-0.028 (0.052)	-0.089 (0.134)	-0.009 (0.069)	-0.004 (0.071)
Δ Sentiment	-0.006*** (0.002)	-0.006*** (0.002)	0.0001 (0.001)	0.0001 (0.001)
U.S. CMBS Spread	0.149*** (0.018)	0.200 (0.195)	0.045** (0.018)	0.043* (0.024)
TED Spread	-6.287*** (0.927)	-9.500* (5.614)	-1.746* (0.898)	-1.660 (1.096)
$\Delta \overline{GDP}$	1.714*** (0.232)	3.060 (2.561)	1.662*** (0.307)	1.650*** (0.462)
$\Delta \overline{StockReturns}$	0.296*** (0.071)	0.365*** (0.094)	0.310*** (0.076)	0.321*** (0.062)
Crisis Dummy	-0.027 (0.025)	-0.053 (0.214)	-0.049* (0.026)	-0.042 (0.044)
Δ Exchange Rate	-2.443*** (0.530)	-4.029* (1.139)	-1.709*** (0.618)	-1.723*** (0.632)
Observations	464	464	368	368
Fixed Effects	Yes	Yes	Yes	Yes
Pesaran CD	19.83***	32.86***	18.65***	18.59***
Adj.- R^2	0.678	0.612	0.635	0.636

Figure A.1: Comparison of PMA with NCREIF

This figure shows the variation of commercial real estate market returns (office and retail) from 2000 to 2015. This sample restriction is in line with the data availability of the SRISK measure and corresponds to the sample we use in the analysis. The plot compares NCREIF NPI returns with the PMA series. We compute annualized average returns of the quarterly NPI index from U.S. Metropolitan Statistical Areas (MSAs) in our sample. Returns are measured in decimals.

Panel A: Office Market (U.S. NCREIF NPI versus PMA)



Panel B: Retail Market (U.S. NCREIF NPI versus PMA)

