Bank Systemic Risk Exposure and Office Market Interconnectedness*

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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. Office 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.[1] The undercapitalization of banks triggers a devaluation of financial but also real assets, which are owned and leased by financial institutions in financial centers.[2] 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.

We offer important insights into the fragility of commercial property markets in financial centers, particularly at times when financial institutions are exposed to valuation shocks. Real estate markets are extremely vulnerable to shocks when property prices are inflated and yields are low. As a consequence, risk spillovers in the global banking sector lead to correlated risk in international office property markets. We apply a spatial econometric model to test whether the common systemic risk of financial institutions in global financial centers leads to cross-sectional return dependence, i.e., correlated risk, of underlying commercial real estate markets.

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 systematic differences in the return dependence among commercial

[1]For instance, office properties in America, Europe, and Asia-Pacific make up 25%, 43%, and 53% of their 2018 transaction volume of income properties, respectively, including the residential sector (PwC and the Urban Land Institute (2019)).

[2]The literature does not offer a unique definition of financial centers. Some 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 global financial centers. Kindleberger (1974) defines financial centers as a concentration of financial activity gaining from network effects, informational economies of scale, and direct interaction with trading partners (see also, e.g., Gehrig (2000), Lizieri (2009)). Motivated by Cetorelli and Peristiani (2013), we define cities as financial centers, if they host a national stock exchange as proxy for the attractiveness of a nearby-located financial service industry.

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 Brownlees and Engle (2017) expected capital shortfall of financial institutions (SRISK) 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 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 as systemic risk channel for financial center office market interconnectedness. During periods of financial distress, when market prices fall, a capital shortfall affects financial institutions' balance sheets. Hence, systemic risk should trigger cross-sectional dependence within commercial real estate office markets in financial centers, due to the simultaneity of potential fire-sales, insolvencies in the financial sector, and revaluations of office properties, which are owned, financed, or occupied by the banking sector (e.g., Lizieri, Baum, and Scott (2000), Lizieri and Pain (2014)). During normal times, banks are less exposed to valuation shocks and the expected undercapitalization given 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 expected, office market co-movements 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 return dependence among retail markets. Our findings hold conditional on 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 control for alternative channels, such as macroeconomic fundamentals or credit availability. For instance, correlated risk in financial center office markets might emerge from employment risk, i.e. potential job cuts and reduced office space demand during periods of financial distress (Hendershott, Lizieri, and Matysiak (1999)), or from a dry-out of global funding liquidity (Davis and Zhu (2011)). Correlated risk also prevails conditional on alternative channels of cross-sectional dependence among international real estate, such as global GDP trends (Case, Goetzmann, and Rouwenhorst (2000)). Potential concerns about omitted sources of cross-sectional dependence can also be mitigated by our double counterfactual approach, as we observe no correlated risk in the retail sector or among office markets during normal times.

As an additional robustness test, we observe no 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 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, correlated risk among international financial center office markets does not pick up other crisis effects than the systemic risk channel during the global banking crisis. For instance, office market returns are not interconnected 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 dot-com bubble was related to overvalued technology companies (e.g., Ofek and Richardson (2003)). Its burst in 2000 potentially led to a lower demand of stock exchange services, but not implied correlated risk.

In the first step of the empirical strategy, our spatial model shows the immediate effect of the valuation shock leading to correlated risk because of the interconnectedness of financial center office markets. In the second step, we apply difference-in-difference models to quantify the impact of systemic risk on the office market return performance. Accompanied by the correlated risk during the crisis period, we show a statistically significant decline in office market returns in comparison to the 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.

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. The literature is mostly silent on co-movements among commercial real estate markets. Exceptions are Case, Goetzmann, and Rouwenhorst (2000), who explain property market co-movements by a global business cycle trend, or Stevenson, Akimov, Hutson, and Krystalogianni (2014), who find evidence of synchronized office market cycles. Our findings relate office market co-movements to systemic risk in interconnected financial centers, suggesting that risk diversification strategies among financial center office markets and across asset classes lose their effectiveness in crisis times when financial protection is most needed.

We also build on the systemic risk literature which is based on correlated asset prices in financial institutions' balance sheets (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 of financial center office markets due to valuation shocks during periods of financial distress. We contribute to the literature which highlights the intertwined fragility of commercial real estate and the banking sector. Correlated risk in commercial real estate office markets further has the potential for reinforced valuation shocks on undercapitalized banks, using real estate as collateral, and thus, threatening the financial stability of the global banking system (e.g., Koetter and Poghosyan (2010), Antoniades (2019)) and the real economy (Chaney, Sraer, and Thesmar (2012)). Our results are also 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.

In spatial econometrics, interconnectedness is often defined as geographic proximity (LeSage and Pace (2009)). In contrast, our approach is motivated by Corrado and Fingleton (2012) who propose spatial linkages based on testable economic channels. We contribute to the spatial econometric literature on economic measures to analyze dependence in global asset markets and systemic risk spillovers in the banking sector (e.g., Asgharian, Hess, and Liu (2013), Eder and Keiler (2015), Milcheva and Zhu (2016), Blasques, Koopman, Lucas, and Schaumburg (2016), Debarsy, Dossougoin, Ertur, and Gnabo (2018)).

The remainder of the paper is structured as follows. Section 2 provides the conceptional 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 2007/2008 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 (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 global 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 decline, which affected the net worth of financial institutions due to the marked-to-market valuation of assets in their balance sheets and again reinforced systemic risk.

To illustrate how soaring systemic risk affects yields of commercial real estate, particularly office markets in financial centers, we use the simple framework of Duca and Ling (2020):

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

where the expected yield, represented by the capitalization rate (cap) and defined as ratio of the contractually fixed rent cash flow ($\overline{NCF}$) relative to the market value (V), can be explained by the risk-free rate (r_F), a required risk premium (rp), long-term rent growth (g), and funding liquidity ($liq^{funding}$).

A high expected capital shortfall during financial crisis periods leads to an undercapitalization of the banking sector. 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)). During periods of financial distress, office property market values $V = \frac{\overline{NCF}}{cap}$ devaluate at still contractually fixed rent cash flows because of capital shortage triggered by insolvencies in the financial service sector, potential fire-sales, and asset price declines when banks readjust real estate values on their balance sheets.

At the same time investors lower their expectations on office market returns, i.e. capitalization rates increase and property values depreciate. This devaluation is driven by the systemic risk or the expected shortfall of the banking sector. 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 reflected in the risk premium and unrelated to macroeconomic conditions, growth of future rents, and credit availability. In the empirical framework, we control for these alternative channels. For instance, 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. Similarly, tightening credit supply and lending standards dried-up the funding liquidity (Duca and Ling (2020)).

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 correlated risk in international office markets. The massive devaluation of office properties is expected to be stronger in local office markets accommodating more systemically relevant banks, as financial institutions have to readjust their real estate assets on their balance sheets. For our identification strategy, we therefore derive the following testable hypothesis:

Hypothesis 1a: *Because of the direct exposure of systemically relevant financial institutions to overvalued assets, leading to a revaluation of underlying office properties owned, financed, and used by the financial sector, we expect correlated risk to occur only in financial center office markets.*

We expect that the systemic risk channel is only effective, i.e. leads to correlated risk among international financial center office markets, during the global financial crisis when banks hold exposure to overvalued assets, and thus, contagious spillovers to the global financial system were the highest (Aoki and Nikolov (2015)). In contrast, the dotcom bubble burst mainly triggered financial losses among ordinary savers due to their exposure to overvalued technology companies (e.g., Ofek and Richardson (2003)), however, with little contagious effects among financial institutions. Furthermore, 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)).

Hypothesis 1b: *As the systemic risk channel on commercial real estate is triggered by a valuation shock of the international banking sector, these co-movements should only be observed during the global financial crisis 2007/2008 as period of financial distress.*

In the empirical analysis, we model correlated risk in terms of return co-movements or cross-sectional dependence by utilizing spatial econometrics.

We assume the highest depreciation of real estate values during the 2007-2008 financial crisis in global financial center office markets. Office space in financial centers is concentrated among financial service firms and its demand is highly connected to the performance of capital markets. Hence, a devaluation shock should reduce returns in financial center office markets more than in the retail sector and in non-financial center office markets. This leads us to the following hypothesis:

Hypothesis 2: *The devaluation effect and the resulting correlated risk in financial center office markets should be accompanied by a significant decline in their market performance compared to the retail sector and office markets in non-financial centers.*

We apply a difference-in-difference model to quantify the devaluation of office properties in financial centers during financial distress periods relative to the counterfactual retail sector and non-financial center office markets.

3 Data

Sub-Section 3.1 describes our commercial real estate data. Sub-Section 3.2 shows how we compute the aggregated systemic risk in financial centers. Sub-Section 3.3 presents the control variables.

3.1 Commercial Real Estate Data

Property Market Analysis (PMA) provides annual city-level commercial real estate returns. We use office and retail market returns from 61 cities in 28 countries from North America, Europe, and Asia-Pacific. To the best of our knowledge, this sample contains the largest cross-section of international city-level returns from 2000 to 2015.[3] PMA constructs total market returns reflecting both rental income and capital growth. The property price is computed from actual annual prime rents per square meter divided by the current market yield taking into account depreciation and management costs. Capital growth is defined as the change between consecutive annual property values divided by the previous market value. The income component is calculated as the ratio of the annual rent and the previous property value.

As a quality check, we compare our data 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).[4] At the Metropolitan Statistical Area (MSA), average PMA market returns are comparable to the annualized quarterly mean 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

[3]For example, Real Capital Analytics (RCA) started to release international commercial real estate data in 2007, which does not provide sufficient time variation for studying differences in office market interconnectedness between normal and turmoil periods, such as the dotcom bubble burst 2000/2001 or the global financial crisis 2007/2008. The time dimension of our sample is restricted by the availability of SRISK data, starting in 2000. However, historic returns of our PMA data go back to 1995 and are utilized in Sub-section 5.3 to quantify the devaluation effect.

[4]In Table A.1 in the Internet Appendix, we compare their statistical characteristics to validate that our PMA data is qualitatively not worse than the NCREIF benchmark.

index (see, e.g., Geltner (1991), Fisher, Geltner, and Webb (1994)).[5] In contrast, PMA returns are based on a marked-to-market valuation methodology, which raises concerns of negative autocorrelation from return reversals. However, when testing for autocorrelation, we find no statistically significant time lag for both return series. Furthermore, when comparing both data sources, returns are highly correlated (up to 93% and 94.5% for New York and Chicago, respectively). A lower correlation (70% to 80%) can often be found in markets with a low number of quarterly reported properties used by NCREIF, especially in the retail sector.

In a next step, we distinguish between financial and non-financial centers. 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.[6] We rule out offshore financial centers, such as the Cayman Islands or Jersey. Following our definition, financial centers are predetermined and exogenous to the office market performance. Historically, the financial service industry was built near local stock exchanges to benefit from international capital and the floor trading access (Wójcik (2013)). In contrast, survey-based indices, such as the Global Financial Center Index (GFCI), rank cities also based on underlying office market conditions, such as infrastructure and business environment. Using these indices to identify financial centers would violate the exogeneity assumption.

Table 1 reports the summary statistics. Panel A shows mean, standard deviation, as well as minimum and maximum values of financial and non-financial center market returns, when pooled across all cities over the sample period. The performances are comparable with mean returns of 8% over the sample period. Financial centers are slightly

[5]The potential smoothing bias might also be detected when comparing the performance of both data in Figure A.1 in the Internet Appendix. NPI retail market returns are more volatile than PMA returns, which might be due to 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)).

[6]We list all cities in Table A.2 of the Internet Appendix, including the descriptive summary for each city-level sector. Panel A shows the market coverage of financial centers. Panel B presents all non-financial centers. Our empirical results also hold when we define financial and non-financial centers as the upper and lower tercile of cities, ranked according to the average total SRISK.

more volatile with a standard deviation of 16% (relative to 12% for non-financial centers). Panels B and C additionally separate between sectors and distinguish between turmoil and normal periods, respectively. Office market returns are lower, accompanied by a higher standard deviation, when compared to the retail sector. The corresponding t-test comparisons reveal statistically significant mean differences between both sectors in financial and non-financial centers. We find similar results when we compare normal and turmoil times. The turmoil period contains the dotcom bubble burst (2000-2002), the global financial crisis (2007-2008), and the European sovereign debt crisis (2010-2012), revealing systematically lower average returns, as indicated by the mean t-tests.

[INSERT Table 1 HERE]

Relation to Stock Markets. We use annual returns of stock market price indices that are representative for the financial center stock exchanges.[7] Figure 1 compares the property and stock market performance over time. Panels A to C show average market returns pooled across all financial centers for the U.S., Europe, and Asia-Pacific relative to the corresponding average stock market price index changes. The figures are based on local currencies to illustrate the return performance, unaffected by local currency movements relative to the USD.[8] Office and retail markets follow a common cyclical pattern with the average stock market, which is in line with Quan and Titman (1999). 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 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

[7] Table A.2 of the Internet Appendix presents the stock market indices and the corresponding platforms.

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

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. 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, 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 declines immediately. 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 panel VAR suggests 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.[9]

To compute the aggregated expected capital shortfall in each financial center, we use the Brownlees and Engle (2017) SRISK measure of international financial institutions from 2000 to 2015.[10] SRISK quantifies the dollar-denominated expected capital shortfall

[9]Given 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.

[10]The data is provided by the NYU Stern Volatility Lab. Table A.3 of the Internet Appendix provides a snapshot of financial institutions with the highest SRISK level, 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)). 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.

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:

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

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 $t + h$.[11] 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 (headquarters, branches, or subsidiaries) in the financial center

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

To identify the main office locations of financial institutions, we use their corresponding SWIFT codes.[12] Figure 3 illustrates the distribution of the financial institutions among financial centers.

[11]Following 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.

[12]The 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.

[INSERT Figure 3 HERE]

Since the SRISK measures are denominated in USD, we can aggregate the expected capital shortfall of the financial institutions. Figure 4 illustrates the performance of the aggregated SRISK measure. Panel A ranks the financial centers with the highest average SRISK from high (London, Hong Kong, and Singapore) to low (Madrid, Amsterdam, and Luxembourg). Following the 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 centers according to the GFCI and the Xinhua/Dow Jones International Financial Centers Development Index. Panel B of Figure 4 shows the cross-sectional average city-level SRISK 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 different between office markets in financial and non-financial centers. 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 controls 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 the impact of macroeconomic fundamentals on the income-potential of commercial real estate (e.g., Ling and Naranjo (1997)). We add house price returns to control for 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 (2020)). The empirical analysis 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. Currency fluctuations also reflect the relative economic attractiveness of a country (Aizenman and Jinjarak (2009)). At the city-level, population growth controls for different real estate demand in cities whereas construction rates in the office and retail sector capture the supply heterogeneity of building stock within a city (DiPasquale and Wheaton (1992)).

We control for returns of domestic real estate investment trusts (REITs) to rule out that the correlated risk is driven by publicly listed real estate companies (Hoesli and Oikarinen (2012)). Using daily data, we calculate the annual correlation between the local stock market return and the global MSCI world index as a proxy for financial market integration (Lehkonen (2015)). Banks might prefer to locate their branches in financially integrated cities, which could be a potential source for related office market co-movements.

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),

[13] Table A.4 in the Internet Appendix provides the definition of all variables. Tables A.5 and A.6 show the descriptive summary and the correlation structure of the covariates.

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 (Ling, Naranjo, and Scheick (2014)).

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, reflected in the term spread, and the CMBS spread, we include the TED spread 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:

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

[14] Table A.7 of the Internet Appendix reports regression results to show how aggregated SRISK in financial centers is related to bank-specific risk factors. Coefficients are statistically significant for the CMBS spread as well as the short-term and long-term interest rate, which are explicitly (U.S. CMBS spread) or implicitly (term spread, TED spread) included as controls in our models.

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 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 account for potential cross-sectional residual correlation.

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

$$w_{ij,t} = \sum_{l} \mathbb{1}\big(main\ office_{il} \cap main\ office_{jl}\big) \times \%SRISK_{l,t}, \tag{5}$$

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. We multiply each indicator variable with the percentage SRISK ($\%SRISK_{l,t} > 0$) of the financial institution l in year t to capture the firm's contribution to the 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.[17]

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. However, the interconnectedness also depends on their common systemic risk contribution, which only includes systemically relevant financial institutions. Hence, potential banks with main offices in Osaka and other financial centers, but with an expected capital

[15] $\%SRISK$ is comparable to ΔCoVaR, giving the tail dependency between a firm and the financial system. It indicates how systemic risk of the overall system is related to the distress of the individual institution.

[16] The importance of the $\%SRISK$-weighting is further motivated in Sub-section 5.3, 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 regression results are merely driven by the binary interconnectedness structure of the weighting matrix. The $\%SRISK$-weighting has an additional meaning.

[17] We also row-normalize the weights to interpret the spatially lagged dependent variable as the weighted average of office markets. As established in the spatial econometric literature (e.g., LeSage and Pace (2009)), 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.

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 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. 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, transmitted to the banking sector, and then affected the markets for stocks and commercial real estate (see, e.g., Brunnermeier (2009) and Levitin and Wachter (2013)).

We estimate our spatial lag model for financial center office market returns during the sample period from 2000 to 2015. However, we first impose restrictions in the time-varying weighting matrix such that all spatial weights are set equal to zero during normal financial market periods. Hence, we only allow for time-varying weights during the 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 a second step, we then 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.

Second, we test for cross-sectional dependence among financial center retail markets as within-city counterfactual. Both sectors are driven by similar local market characteristics. 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 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 either affect office market return co-movements also during normal times, or should 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 endogenous office market returns might reflect 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)). Taking into account the dependence from explanatory variables, the specification approximates the Spatial Durbin Model (LeSage and Pace (2009)). The average values capture 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 returns in country i. Hence, 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 to capture 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. This crisis dummy ascertains that the weighting matrix for our systemic risk channel is not overlaid with the level effect on the individual market return, but captures 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 be related to cross-country heterogeneity and differences between office markets, e.g., currency zones, gateway cities, industry decomposition, 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 additionally capture the potential multi-center structure of a city and might be correlated with the spatially lagged dependent variable. For example, gateway cities or technology centers 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 by the within-structure of the fixed effects specification, our model explains the time variation of market returns 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.[18]

[18] 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 systemic risk in financial centers as a transmission channel for related office market return co-movements. Sub-Section 5.2 presents additional robustness tests. Sub-Section 5.3 applies difference-in-difference models to quantify the impact on office market returns during turmoil times relative to the counterfactual retail sector and compared to non-financial center office markets.

5.1 Systemic Risk as Transmission Channel

Table 2 shows different model specifications of Equation (4). We use Model I as the baseline model and Models II and III for robustness. We include all cities as financial centers in which a national stock exchange trading platform is located. Our findings suggest spatial dependence among financial center office markets (*Office*) during periods of financial distress (*Turmoil*), which can be related to the common systemic risk in the banking sector. We allow for time-varying weights for the global financial crisis period 2007/2008 and restrict them 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 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. 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 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]

We use contemporaneous covariates in our model to rule out that the observed spatial dependence might arise from omitted common risk factors or macroeconomic fundamentals. As can be seen from the separate regressions, the control variables receive slightly different parameter estimates for the retail and office sector, suggesting different exposure to common fundamentals.

The models control for the positive relation between office markets and the underlying stock market performance in financial centers. Model I implies that a 1%-change in 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, 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 find no statistically significant relation between the aggregated level of expected capital shortfall of the banking sector in the financial center and the related office market. Intuitively, a higher office market exposure to the hypothetical undercapitalization of the local banking sector might have a dampening effect on expected rental cash flows. Yet, the effect is economically insignificant. We 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.[19] 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. In normal times, the SRISK level in financial centers reflects only a hypothetical effect.

Model I 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 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 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

[19]The variable $log(SRISK)$ differs from the transmission channel captured in the weighting matrix. Total SRISK measures the expected capital shortfall of the local banking sector, whereas the weights reflect 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 overfitting.

variable $\Delta Claims$ reflects the potential effect on property markets coming from international bank lending activity (e.g., Davis and Zhu (2011)). To capture the reflection problem, we control for the average stock market return and the global GDP growth as a potential driver for the correlation among international property markets (see, e.g., Case, Goetzmann, and Rouwenhorst (2000)). The crisis dummy disentangles the crisis-related level effect from correlated risk.[20]

The results hold, when we include additional control variables. Model II reveals the exposure of commercial real estate markets to the performance of mortgage-backed securities and investor sentiment. The positive relation between office market returns and the U.S. CMBS spread can be interpreted in terms of higher risk premiums. Our findings also 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 real estate assets. Model III additionally captures the TED spread as proxy for the overall global interbank credit risk (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 Additional Robustness

Our findings are robust against alternative channels. In Panel A of Figure 7, we show the magnitude of the spatial lag coefficients and the corresponding 95% confidence intervals for each model, when we control for additional variables.[21] Conditional on the additional covariates, we still find cross-sectional dependence among financial center office markets during the global financial crisis. The spatial lags are again insignificant during normal times and for the counterfactual retail sector.

[20] In Table A.8 in the Internet Appendix, we replicate our results without the crisis dummy to illustrate that this variable does not remove potential correlated risk in the counterfactual retail sector or during normal times, which would translate in a statistically significant spatial lag.

[21] To conserve space, we present the regression results in Tables A.9 to A.12 in the Internet Appendix.

[INSERT FIGURE 7 HERE]

First, the findings reveal correlated risk among financial center office markets during turmoil times, which is still statistically significant at the 10% level, when we control for city-level unemployment rates. The employment channel as contractual counterparty risk in global office markets might be reinforced during periods of financial distress, leading to potential job cuts and lower demand for office space in the banking sector (see, e.g., Hendershott, Lizieri, and Matysiak (1999)). Due to data limitations, we do not include this variable in the baseline model.

We also capture the potential impact of conventional and unconventional monetary policy on global commercial real estate markets to further control for the funding liquidity channel (Duca and Ling (2020)). Instead of the term spread, we use the short-term interest rate level as proxy for the financing costs of commercial real estate, which is confirmed by the negative relation with property returns. Due to limited data availability in some countries, the short-term rate is used as risk-free proxy instead of more appropriate long-term mortgage rates. Similarly, unconventional monetary policy tools after the financial crisis, i.e., a sharp increase in quantitative easing, as proxied by central bank assets as a share of GDP, do not affect our results on correlated risk.

A potential concern could also be that, by construction, financial institutions' SRISK depends on the performance of the MSCI world equity index as an omitted factor. We show that even after controlling for global MSCI world equity index market returns, our transmission channel of common systemic risk among financial centers prevails and implies statistically significant return co-movements among the related office markets during turmoil periods.

The baseline models include cross-sectional averages of GDP growth and stock market returns to account for the reflection problem. Both common factors might capture some of the variation coming from an omitted property-specific global market factor. To fully preclude that the spatial weights reflect the impact of the overall property market portfolio, we first regress market returns on their sector-specific global market portfolio.[22] In a second step, we then use the residuals as endogenous variable to re-estimate the spatial lag models. We conclude that correlated risk does not merely reflect a global property market portfolio, but can be explained by the systemic risk channel from the interconnected financial system.

Panel B shows that the results are also robust against different specifications of the weighting matrix. Correlated risk in financial centers might not be driven by systemic risk, but by the systematically larger amount of financial institutions based on which the expected capital shortfall is aggregated. For instance, the overall expected capital shortfall in large financial centers might actually depend on the number of located banks. To address this concern, we first show that the findings hold when we normalize the weights, i.e., divide them by the number of located banks. Second, we find similar results when we give those linkages between financial centers with more financial institutions a larger weight. Hence, instead of dividing by the number of banks, we multiply the spatial weights with the corresponding amount of located banks. As indicated by the results, we can also rule out that financial centers with many systemically relevant banks might reveal a stronger return dependence among related office markets.

We also confirm our findings when we use a less restrictive definition of financial centers. In an additional robustness test, we rank all cities in our sample according to their average total systemic risk level and define the upper tercile of cities as financial centers. Correlated risk among financial center office markets is still statistically significant at the 10% significance level.[23]

As an additional robustness test, we replicate our findings when we implement the spatial weights based on the marginal expected capital shortfall (MES) proposed by

[22]For the corresponding global property market portfolios, we estimate factor loadings of 1.15 (office) and 1.17 (retail). We also find correlations up to 65% and 77% between the equally-weighted property market portfolio and the common factors.

[23]We show the regression results in Table A.13 in the Internet Appendix. Top tercile SRISK cities are listed in Panel A of Figure 4, additionally including Brussels, Dublin, Vienna, and Zurich.

Acharya, Pedersen, Philippon, and Richardson (2017), as alternative systemic risk measure. Instead of multiplying the indicator variables in the spatial weights with $\%SRISK$, we aggregate the individual MES of financial institutions. As our weighting structure depends on the overall systemic risk level in a financial center, we have to rely on systemic risk measures, which allow for aggregation.

Non-Financial Centers. Next, in Table 3 we re-estimate the spatial models for 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. As expected, we find no statistically significant correlated risk, or office market co-movements, in non-financial centers implied by the common systemic banking sector risk. Following the 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.[24]

[INSERT TABLE 3 HERE]

As a potential limitation, the selection of non-financial centers is restricted by PMA data availability. To further improve the comparability between available financial and non-financial center office markets in our sample, we apply a propensity score matching approach. As matching variables, we use city-level information on population growth, construction activity, as well as GDP growth per capita, which we additionally collected for most cities in our sample from 2002 to 2015. We also use the short-term interest rate as a matching variable to allow for a direct within-country comparability between financial and non-financial centers and to capture the homogeneity of countries affected by the same

[24]Table A.13 in the Internet Appendix confirms our results when we use cities from the bottom tercile with the lowest SRISK level as non-financial centers, also including the cities Boston, Chicago, and Washington.

monetary policy regime. Our choice of matching variables is motivated by DiPasquale and Wheaton (1992), reflecting macroeconomic fundamentals, the development sector, and financing costs as potential drivers of real estate markets. Additionally, we construct a dummy variable based on nearby located top universities as proxy for knowledge and technology hubs (Audretsch and Feldman (1996)). This pre-determined variable allows to match cities based on their classification as multi-functional centers and technology hubs.[25] Table 4 reveals that we still find no evidence of correlated risk among the matched sample of non-financial centers. The findings also prevail when we replicate the models with all available non-financial centers before matching, also including the cities Boston, Chicago, San Francisco, and Washington.

[INSERT TABLE 4 HERE]

Placebo Tests with 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. Model I uses the established weighting matrix based on the interconnectedness between all financial centers in the sample. Model II replicates the results with spatial weights based on a subsample of cities, which were specifically affected by the corresponding crisis. Applying the same identification strategy, we allow the weights to vary during the turmoil period and restrict them to zero in normal times.

For the sovereign debt crisis, Model I compares the spatial dependence across financial center office markets with the counterfactual retail sector for the crisis period from 2010 to 2012. As expected, the results reveal no correlated risk, when the European sovereign debt crisis hit the banking sector. Specifically, the sovereign debt crisis

[25] Panel A of Figure A.2 in the Internet Appendix shows the histograms of the estimated propensity scores before and after matching. Panel B compares the average values of each variable for financial (treated) and non-financial centers (control group) plotted against the propensity score. Both graphs show the improved common support after matching. Similarly, Table A.14 shows average values for all matching variables and the corresponding t-test mean differences between treated and control group before and after the matching. The comparability can be improved for all variables, except for construction activity, which differs between both groups and is therefore included as covariate in the model.

was mainly confined to Ireland and Southern European countries, such as Italy, Portugal, Spain, and particularly Greece (Lane (2012)). Model II confirms the results, when we only allow for interconnectedness between those affected countries, restricting the spatial weights to zero for all other countries.

We also find no evidence of correlated risk during the dotcom bubble burst 2000 to 2002.[26] The result presented in Model I for the dotcom bubble is in line with Aoki and Nikolov (2015). 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. Model II indicates no correlated risk for the dotcom bubble burst when we specify the interconnectedness only between countries with more extreme stock market declines observed during the burst than the downside risk threshold of -0.24% based on mean and standard deviation of the MSCI world index.

[INSERT TABLE 5 HERE]

5.3 Quantifying the Devaluation Shock

Sub-section 5.1 shows empirical evidence of correlated risk in financial center office markets during the global financial crisis period, triggered through the systemic risk channel. In this subsection, we quantify the entire effect of the immediate valuation shock on financial center office markets relative to the counterfactual retail sector and non-financial office markets.

Office versus Retail Markets in Financial Centers. If the common systemic risk in the banking sector negatively affects the office market performance in financial centers, we should observe a significant return decline in the aftermath period 2008/2009

[26] The findings remain insignificant when we re-estimate the spatial lag models for both crisis periods, but restrict the corresponding turmoil periods to shorter time windows, e.g., only using 2000/2001 for the dotcom bubble burst and 2010/2011 for the Sovereign debt crisis, respectively.

relative to the counterfactual retail sector. We exploit the global financial crisis period as shock to compare the return performance of both sectors within financial centers. We specify the following linear difference-in-difference model

$$r_{it} = \beta_0 + \beta_1 D_{Crisis} + \beta_2 D_{Office} + \beta_3 (D_{Crisis} \times D_{Office}) + X_{it}\beta + \epsilon_{it}, \tag{6}$$

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.

Model I of Table 6 estimates the difference-in-difference model. We find a statistically significant coefficient of -0.088 for the interaction term between the global financial crisis aftermath 2008/2009 and the office market dummy. The negative coefficient suggests that the asset price bubble burst results in an average annual decrease in office market returns of 8.8%-points compared to the counterfactual retail sector. Given the within-city comparison between office markets and the retail sector, common factors should be removed by the difference-in-difference structure.[27] However, to further reduce a potential bias in the estimated interaction term, we control for the established covariates from our baseline spatial model. Model II confirms our findings with a coefficient estimate of -0.080. This specification includes *city* $\times$ *year* fixed effects as a generalization of the difference-in-difference model to address the potential omitted variable bias (Angrist and Pischke (2009)). We use *city* $\times$ *year* dummy variables to additionally control for observable and unobservable factors which might explain office market returns.

We also replicate both model specifications for the sovereign debt crisis and the dotcom bubble burst. To analyze the impact of the European sovereign debt crisis, we split

[27]Table A.16 in the Internet Appendix re-estimates the difference-in-difference model for a placebo test for the years 2004 and 2005 to show that both sector performances are not significantly different prior to the global financial crisis.

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 and 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.[28] We find a significant impact of -0.057 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. However, due to data limitations on our control variables prior to the sample period starting in 2000, we abstain from interpreting the difference-in-difference specification (Model I) for the dotcom bubble burst. Instead, we refer to the *city* $\times$ *year* fixed effects specification (Model II), which provides a comparable estimate on the interaction term.

[INSERT TABLE 6 HERE]

Financial versus Non-Financial Center Office Markets. We also compare office market returns between financial and non-financial centers and test whether the exposure to a higher agggregated SRISK level leads to stronger return declines during the global financial crisis. To clearly distinguish between financial and non-financial centers, we exclude the cities of Boston, Chicago, San Francisco, and Washington. To be consistent with the definition used for the spatial models, we do not use them as non-financial centers, as these cities are ranked as financial centers by the GFCI. However, we include them in an additional robustness test when we allow for a less restrictive definition of financial

[28]Note that the PMA sample is now not restricted by availability of the SRISK measure, so that the starting year 1995 of the full sample can be used.

centers, based on the aggregated SRISK level.

In a first step, we follow a similar difference-in-difference approach from the previous sector analysis comparing office market performances in financial and non-financial centers. For instance, Model I in Table 7 suggests that office market returns in financial centers decrease by 9%-points more 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 dotcom bubble burst. We control for city-level heterogeneity in the construction sector and population growth, as well as additional national macroeconomic control variables to remove potential differences between financial and non-financial centers in different countries. The findings are confirmed by the $city \times year$ fixed effects specification (Model II). Although we control for fixed effects or include country-level covariates, we do not have sufficient city-level controls to capture all systematic 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 models as a mean comparison approach between both office market types.

[INSERT TABLE 7 HERE]

We then extend our analysis on office market returns and study whether a higher SRISK exposure is related to stronger declines 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. Cross-sectional regressions in Table 8 show 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. Because we are interested in the cross-sectional variation of market returns, we do not include individual fixed effects.

We distinguish between office markets 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 dummy for 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 -21% for office markets in cities with a banking sector that belongs to the group with the 25% highest expected capital shortfall. 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.

Finally, Model VI tests whether cities defined as technology centers are less affected by systemic risk during crisis periods. We specify an interaction term between the variable $SRISK_{high}$, the financial crisis dummy, and the dummy equal to 1 if a top university is located in close proximity to the center. While office market returns are significantly higher in technology centers, we do not find a statistically significant interaction term between the variables. Hence, we conclude that multi-functional centers, i.e., proxied by top university locations, are not less affected by systemic risk.[29]

[INSERT TABLE 8 HERE]

6 Conclusion

This paper tests for the systemic risk of financial firms between local banking sectors as a source of return co-movements among global financial center office markets. We first quantify the overall expected uncercapitalization of the banking sector in financial centers.

[29]We confirm this finding in Panel E of Table A.15 in the Internet Appendix, when we re-estimate the spatial models and give linkages between multi-functional centers the largest weight to test whether technology centers are less exposed to systemic risk. While we still observe correlated risk among financial center office markets during periods of distress, the estimated spatial lag coefficient is comparable to the baseline results. Hence, we conclude that the degree of correlated risk is not different when specifically accounting for technology centers.

In a second step, we test for cross-sectional dependence among financial center office markets during financial turmoil periods, when a substantial decline in stock market prices leads to an immediate valuation shock on the balance sheet of financial firms with main offices in different financial centers. We exploit the global financial crisis in 2007/2008 as a banking crisis with substantial exposure to the U.S. housing market bubble.

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. The return dependence cannot be observed during normal times as a placebo test. Our findings further suggest no co-movements among financial center retail markets as within-city counterfactual 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 offer important implications for regulatory authorities and policy makers. First, we provide new insights into the interconnectedness of seemingly unrelated local office markets due to the systemic risk exposure of globally interconnected banks. Systemic risk as a transmission channel for correlated office market risk in financial centers and co-movements with other assets in periods of financial distress has additional risk management implications for investors. Second, considering systemic risk and banking crises in isolation from related commercial real estate neglects the vulnerability of the banking sector from reinforced valuation shocks and risk spillovers on undercapitalized banks with office property value on their balance sheets. Third, we quantify the overall expected capital shortfall in financial centers, which can be used as a macroprudential tool for assessing financial costs of bail-out strategies and to implement implied linkages and risk spillovers in stress tests when studying the economic consequences of systemic shocks on the financial stability.

References

Acharya, V., R. Engle, and M. Richardson (2012): "Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks," *American Economic Review: Papers & Proceedings*, 102(3), 59–64.

Acharya, V., L. Pedersen, T. Philippon, and M. Richardson (2017): "Measuring Systemic Risk," *Review of Financial Studies*, 30(1), 2–47.

Adrian, T., and M. Brunnermeier (2016): "CoVaR," *American Economic Review*, 106(7), 1705–1741.

Aizenman, J., and Y. Jinjarak (2009): "Current Account Patterns and National Real Estate Markets," *Journal of Urban Economics*, 66, 75–89.

Allen, F., A. Babus, and E. Carletti (2012): "Asset Commonality, Debt Maturity, and Systemic Risk," *Journal of Financial Economics*, 104(3), 519–534.

Angrist, J., and J.-S. Pischke (2009): *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton University Press: Princeton NJ.

Antoniades, A. (2019): "Commercial Bank Failures During The Great Recession: The Real (Estate) Story," *Working Paper.*

Aoki, K., and K. Nikolov (2015): "Bubbles, Banks and Financial Stability," *Journal of Monetary Economics*, 74(C), 33–51.

Arellano, M., and S. Bond (1991): "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies*, 58(2), 277–297.

Arellano, M., and O. Bover (1995): "Another Look at the Instrumental Variable Estimation of Error-Components Models," *Journal of Econometrics*, 68(1), 29–51.

Asgharian, H., W. Hess, and L. Liu (2013): "A Spatial Analysis of International Stock Market Linkages," *Journal of Banking and Finance*, 37(12), 4738–4754.

Audretsch, D., and M. Feldman (1996): "R&D Spillovers and the Geography of Innovation and Production," *American Economic Review*, 86(3), 630–640.

Begenau, J., M. Piazzesi, and M. Schneider (2015): "Banks' Risk Exposures," *NBER Working Paper.*

Bekaert, G., M. Ehrmann, M. Fratzscher, and A. Mehl (2014): "The Global Crisis and Equity Market Contagion," *Journal of Finance*, 69(6), 2597–2649.

Bekaert, G., C. Harvey, and A. Ng (2005): "Market Integration and Contagion," *Journal of Business*, 78(1), 39–70.

Benoit, S., J.-E. Colliard, C. Hurlin, and C. Pérignon (2017): "Where the Risks Lie: A Survey on Systemic Risk," *Review of Finance*, 21(1), 109–152.

Blasques, F., S. Koopman, A. Lucas, and J. Schaumburg (2016): "Spillover Dynamics for Systemic Risk Measurement Using Spatial Financial Time Series Models," *Journal of Econometrics*, 195(2), 211–223.

Brownlees, C., and R. Engle (2017): "SRISK: A Conditional Capital Shortfall Measure of Systemic Risk," *Review of Financial Studies*, 30(1), 48–79.

Brunnermeier, M., S. Rother, and I. Schnabel (2019): "Asset Price Bubbles and Systemic Risk," *Review of Financial Studies*, Forthcoming.

Brunnermeier, M. K. (2009): "Deciphering the Liquidity and Credit Crunch 2007-2008," *Journal of Economic Perspectives*, 23(1), 77–100.

Case, B., W. Goetzmann, and K. Rouwenhorst (2000): "Global Real Estate Markets: Cycles and Fundamentals," *NBER Working Paper Series*, 7566.

Cetorelli, N., and S. Peristiani (2013): "Prestigious Stock Exchanges: A Network Analysis of International Financial Centers," *Journal of Banking and Finance*, 37(5), 1543–1551.

Chaney, T., D. Sraer, and D. Thesmar (2012): "The Collateral Channel: How Real Estate Shocks Affect Corporate Investment," *American Economic Review*, 102(6), 2381–2409.

Corrado, L., and B. Fingleton (2012): "Where is the Economics in Spatial Econometrics?," *Journal of Regional Science*, 52(2), 210–239.

Davis, E., and H. Zhu (2011): "Bank Lending and Commercial Property Cycles: Some Cross-Country Evidence," *Journal of International Money and Finance*, 30(1), 1–21.

Debarsy, N., C. Dossougoin, C. Ertur, and J.-Y. Gnabo (2018): "Measuring Sovereign Risk Spillovers and Assessing the Role of Transmission Channels: A Spatial Econometric Approach," *Journal of Economic Dynamics and Control*, 87, 21–45.

DiPasquale, D., and W. Wheaton (1992): "The Markets for Real Estate Assets and Space: A Conceptual Framework," *Real Estate Economics*, 20(2), 181–198.

Duca, J., and D. Ling (2020): "The Other (Commercial) Real Estate Boom and Bust: The Effects of Risk Premia and Regulatory Capital Arbitrage," *Journal of Banking and Finance*, Forthcoming.

Eder, A., and S. Keiler (2015): "CDS Spreads and Contagion Amonst Systemically Important Financial Institutions: A Spatial Econometric Approach," *International Journal of Finance and Economics*, 20(4), 291–309.

Fisher, J. D., D. M. Geltner, and R. B. Webb (1994): "Value Indices of Commercial Real Estate: A Comparison of Index Construction Methods," *Journal of Real Estate Finance and Economics*, 9, 137–164.

Gehrig, T. (2000): "Cities and the Geography of Financial Centers," in *The Economics of Cities*, ed. by J. Thisse, and J. Huriot, pp. 415–445. Cambridge University Press.

Geltner, D., and D. C. Ling (2006): "Considerations in the Design and Construction of Investment Real Estate Research Indices," *Journal of Real Estate Research*, 28(4), 411–444.

Geltner, D. M. (1991): "Smoothing in Appraisal-Based Returns," *Journal of Real Estate Finance and Economics*, 4(3), 327–345.

Ghysels, E., A. Plazzi, and R. Valkanov (2007): "Valuation in US Commercial Real Estate," *European Financial Management*, 13(3), 472–497.

Hendershott, P. H., C. M. Lizieri, and G. A. Matysiak (1999): "The Workings of the London Office Market," *Real Estate Economics*, 27(2), 365–387.

Hoesli, M., and E. Oikarinen (2012): "Are REITs Real Estate? Evidence from International Sector Level Data," *Journal of International Money and Finance*, 31(7), 1823–1850.

Kelejian, H. H., and I. R. Prucha (2007): "HAC Estimation in a Spatial Framework," *Journal of Econometrics*, 140(1), 131–154.

Kindleberger, C. (1974): *The Formation of Financial Centers: A Study of Comparative Economic History.* Princeton Studies in International Finance Number 36. Princeton Univeristy Press, Princeton, NJ.

Koetter, M., and T. Poghosyan (2010): "Real Estate Prices and Bank Stability," *Journal of Banking and Finance*, 34(6), 1129–1138.

Lane, P. R. (2012): "The European Sovereign Debt Crisis," *Journal of Economic Perspectives*, 26(3), 49–68.

Lehkonen, H. (2015): "Stock Market Integrtion and the Global Financial Crisis," *Review of Finance*, 19(5), 2039–2094.

LeSage, J. P., and R. K. Pace (2009): *Introduction to Spatial Econometrics*. Boca Raton, Taylor and Francis.

Levitin, A. J., and S. M. Wachter (2013): "The Commercial Real Estate Bubble," *Harvard Business Law Review*, 3(1), 83–118.

Ling, D. C., and A. Naranjo (1997): "Economic Risk Factors and Commercial Real Estate Returns," *Journal of Real Estate Finance and Economics*, 15(3), 283–307.

Ling, D. C., A. Naranjo, and B. Scheick (2014): "Investor Sentiment, Limits to Arbitrage and Private Market Returns," *Real Estate Economics*, 42(3), 531–577.

Lizieri, C. (2009): *Towers of Capital: Office Markets and International Financial Services*. Wiley-Blackwell, Oxford.

Lizieri, C., A. Baum, and P. Scott (2000): "Ownership, Occupation and Risk: A View of the City of London Office Market," *Urban Studies*, 37(7), 1109–1129.

Lizieri, C., and K. Pain (2014): "International Office Investment in Global Cities: The Production of Financial Space and Systemic Risk," *Regional Studies*, 48(3), 439–455.

Manski, C. F. (1993): "Identification and Endogenous Social Effects: The Reflection Problem," *Review of Economic Studies*, 60(3), 531–542.

Milcheva, S., and B. Zhu (2016): "Bank Integration and Co-Movements across Housing Markets," *Journal of Banking and Finance*, 72, S148–S171.

Ofek, E., and M. Richardson (2003): "DotCom Mania: The Rise and Fall of Internet Stock Prices," *Journal of Finance*, 58(3), 1113–1137.

Pesaran, M. H. (2004): "General Diagnostic Tests for Cross Section Dependence in Panels," *Cambridge Working Papers in Economics No. 435 and CESifo Working Paper Series No. 1229*.

Portniaguina, E., and M. L. Lemmon (2006): "Consumer Confidence and Asset Prices: Some Empirical Evidence," *Review of Financial Studies*, 19(4), 1499–1529.

PwC, and the Urban Land Institute (2019): "Emerging Trends in Real Estate: The Global Outlook for 2019," *London: PwC and the Urban Land Institute 2019*.

Quan, D. C., and S. Titman (1999): "Do Real Estate Prices and Stock Prices Move Together? An International Analysis," *Real Estate Economics*, 27(2), 183–207.

Sarafidis, V., and T. Wansbeek (2012): "Cross-Sectional Dependence in Panel Data Analysis," *Econometrics Reviews*, 31(5), 483–531.

Schmeling, M. (2009): "Investor Sentiment and Stock Returns: Some International Evidence," *Journal of Empirical Finance*, 16(3), 394–408.

Stevenson, S., A. Akimov, E. Hutson, and A. Krystalogianni (2014): "Concordance in Global Office Market Cycles," *Regional Studies*, 48(3), 456–470.

Wang, W., and L. F. Lee (2013): "Estimation of Spatial Panel Data Models with Randomly Missing Data in the Dependent Variable," *Regional Science and Urban Economics*, 43(3), 521–538.

Wójcik, D. (2013): "The dark-side of NY-LON: Financial Centres and the Global Financial Crisis," *Urban Studies*, 50(13), 2736–2752.

Table 1: Summary Statistics of Commercial Real Estate Market Returns

This table contains the descriptive summary and mean difference t-tests for commercial real estate market returns. Our sample is pooled over a cross-section of 61 cities in 28 countries from 2000 to 2015. 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 sector (office versus retail) and turmoil versus normal times, respectively. Turmoil periods are the years 2000 – 2002 (dotcom bubble burst), 2007/2008 (global financial crisis), and 2010 – 2012 (sovereign debt crisis). 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	0.16	-0.70	0.79	823
Non-Financial	0.08	0.12	-0.44	0.65	884
Δ t-test	-0.16				
Panel B: Market Returns by Sector					
	Mean	**Std.Dev.**	**Min.**	**Max.**	**Obs.**
Financial					
Office	0.06	0.16	-0.56	0.79	455
Retail	0.10	0.15	-0.70	0.71	368
Δ t-test	-3.83***				
Non-Financial					
Office	0.07	0.13	-0.44	0.65	499
Retail	0.09	0.10	-0.24	0.60	385
Δ t-test	-2.11**				
Panel C: Market Returns by Period					
	Mean	**Std.Dev.**	**Min.**	**Max.**	**Obs.**
Financial					
Turmoil	0.06	0.16	-0.70	0.79	405
Normal	0.10	0.16	-0.55	0.71	418
Δ t-test	-3.85***				
Non-Financial					
Turmoil	0.07	0.13	-0.44	0.60	438
Normal	0.09	0.11	-0.38	0.65	446
Δ t-test	-2.77***				

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 *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.

	Model I				**Model II**				**Model III**			
	Office		**Retail**		**Office**		**Retail**		**Office**		**Retail**	
	Turmoil	**Normal**	**Turmoil**	**Normal**	**Turmoil**	**Normal**	**Turmoil**	**Normal**	**Turmoil**	**Normal**	**Turmoil**	**Normal**
Spatial Lag	0.295**	-0.510	-0.096	0.109	0.325**	-0.487	-0.027	0.011	0.331**	-0.534	-0.011	0.020
	(0.145)	(0.624)	(0.140)	(0.111)	(0.139)	(0.993)	(0.148)	(0.147)	(0.146)	(1.086)	(0.157)	(0.147)
Stock Returns	0.093**	0.105*	0.080*	0.083*	0.083*	0.091*	0.077*	0.078*	0.081*	0.090*	0.076*	0.078*
	(0.047)	(0.057)	(0.044)	(0.043)	(0.043)	(0.050)	(0.044)	(0.044)	(0.043)	(0.051)	(0.044)	(0.044)
log(SRISK)	-0.010	-0.010	-0.006	-0.007	-0.014	-0.016	-0.008	-0.008	-0.015	-0.018	-0.008	-0.008
	(0.011)	(0.014)	(0.010)	(0.010)	(0.010)	(0.015)	(0.010)	(0.010)	(0.010)	(0.013)	(0.010)	(0.010)
ΔGDP Capita	0.663***	0.813***	0.835***	0.813***	0.622***	0.756***	0.814***	0.810***	0.507***	0.586***	0.803***	0.800***
	(0.182)	(0.203)	(0.190)	(0.187)	(0.172)	(0.185)	(0.185)	(0.186)	(0.176)	(0.187)	(0.190)	(0.190)
Term Spread	0.248	0.249	1.047*	0.998*	0.046	-0.076	1.034*	1.056*	0.150	0.092	1.075*	1.060*
	(0.499)	(0.722)	(0.586)	(0.579)	(0.477)	(0.585)	(0.587)	(0.590)	(0.466)	(0.652)	(0.588)	(0.588)
ΔFloor Space	-0.884***	-1.070***	0.019	0.015	-0.723**	-0.841***	0.048	0.047	-0.767***	-0.918***	0.048	0.045
	(0.303)	(0.325)	(0.163)	(0.161)	(0.294)	(0.312)	(0.165)	(0.165)	(0.290)	(0.295)	(0.166)	(0.165)
ΔREIT	0.351	0.697**	-0.138	-0.152	0.199	0.463	-0.175	-0.175	0.167	0.441	-0.171	-0.172
	(0.240)	(0.352)	(0.281)	(0.277)	(0.224)	(0.288)	(0.283)	(0.282)	(0.217)	(0.372)	(0.284)	(0.283)
ΔPopulation	0.077	0.091	0.661	0.600	0.065	0.071	0.844	0.823	0.085	0.105	0.859	0.832
	(0.118)	(0.144)	(0.845)	(0.846)	(0.104)	(0.123)	(0.844)	(0.844)	(0.112)	(0.137)	(0.848)	(0.849)
ΔResidential	0.619***	0.677***	0.465***	0.464***	0.596***	0.654***	0.474***	0.476***	0.576***	0.629***	0.475***	0.474***
	(0.174)	(0.193)	(0.120)	(0.119)	(0.159)	(0.171)	(0.119)	(0.119)	(0.157)	(0.170)	(0.119)	(0.119)
Correlation to MSCI	0.087	0.099	0.103*	0.112*	0.077	0.082	0.101*	0.101*	0.087	0.099	0.102*	0.103*
	(0.066)	(0.078)	(0.060)	(0.060)	(0.064)	(0.075)	(0.061)	(0.061)	(0.062)	(0.072)	(0.061)	(0.061)
ΔClaims	0.008	-0.021	0.006	0.007	0.014	-0.004	0.008	0.008	0.004	-0.023	0.006	0.007
	(0.050)	(0.069)	(0.064)	(0.063)	(0.048)	(0.060)	(0.064)	(0.064)	(0.045)	(0.070)	(0.063)	(0.063)
ΔSentiment					-0.006***	-0.006***	0.0004	0.0004	-0.006***	-0.007***	0.0004	0.0004
					(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
U.S. CMBS Spread					0.086***	0.128	0.025	0.024	0.074***	0.113	0.024	0.023
					(0.016)	(0.100)	(0.015)	(0.016)	(0.015)	(0.096)	(0.015)	(0.016)
TED Spread									-3.015**	-4.842**	-0.233	-0.199
									(0.772)	(2.230)	(0.828)	(0.841)
$\Delta\overline{GDP}$	0.407*	1.205	0.423*	0.315	0.309	0.995	0.398	0.392	0.355	1.146	0.411	0.392
	(0.215)	(0.312)	(0.247)	(0.267)	(0.199)	(1.103)	(0.247)	(0.284)	(0.197)	(1.414)	(0.253)	(0.300)
$\overline{StockReturns}$	0.090	0.195***	0.146***	0.118**	0.079	0.195***	0.131**	0.123**	0.043	0.142**	0.124**	0.120**
	(0.067)	(0.067)	(0.056)	(0.050)	(0.065)	(0.058)	(0.056)	(0.050)	(0.068)	(0.063)	(0.060)	(0.050)
Crisis Dummy	-0.002	-0.0003	-0.021	-0.020	-0.039	-0.045	-0.035	-0.036	-0.034	-0.041	-0.036*	-0.035
	(0.024)	(0.078)	(0.020)	(0.019)	(0.024)	(0.099)	(0.021)	(0.023)	(0.024)	(0.105)	(0.022)	(0.023)
ΔExchange Rate	-0.572	-1.457**	-0.061	-0.018	-0.239	-0.955*	0.035	0.037	-0.092	-0.799	0.038	0.039
	(0.443)	(0.726)	(0.465)	(0.457)	(0.422)	(0.517)	(0.471)	(0.470)	(0.406)	(0.712)	(0.471)	(0.468)
Observations	464	464	368	368	464	464	368	368	464	464	368	368
Fixed Effects	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***	5.24***	5.10***	6.17***	15.20***	5.05***	4.83***
Adj.-R^2	0.486	0.446	0.521	0.525	0.529	0.497	0.517	0.517	0.549	0.528	0.516	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 *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.

	Model I				**Model II**				**Model III**			
	Office		**Retail**		**Office**		**Retail**		**Office**		**Retail**	
	Turmoil	**Normal**	**Turmoil**	**Normal**	**Turmoil**	**Normal**	**Turmoil**	**Normal**	**Turmoil**	**Normal**	**Turmoil**	**Normal**
Spatial Lag	-0.143	0.104	-0.131	0.115	-0.053	0.090	-0.070	0.010	-0.008	0.045	-0.003	0.123
	(0.193)	(0.149)	(0.179)	(0.119)	(0.197)	(0.110)	(0.185)	(0.203)	(0.204)	(0.126)	(0.195)	(0.130)
Stock Returns	0.070	0.066	0.075	0.070	0.056	0.054	0.069	0.066	0.047	0.047	0.061	0.066
	(0.044)	(0.044)	(0.046)	(0.047)	(0.045)	(0.044)	(0.047)	(0.046)	(0.046)	(0.046)	(0.047)	(0.046)
log(SRISK)	-0.001	-0.002	0.001	0.000	-0.003	-0.003	-0.000	0.000	-0.003	-0.003	-0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
ΔGDP Capita	1.168***	1.137***	0.368**	0.361**	1.137***	1.112***	0.365**	0.386*	1.079***	1.072***	0.344**	0.364**
	(0.183)	(0.175)	(0.154)	(0.152)	(0.175)	(0.169)	(0.156)	(0.200)	(0.176)	(0.174)	(0.160)	(0.175)
Term Spread	-1.190**	-1.080**	0.314	0.302	-1.169**	-1.146**	0.366	0.250	-1.031*	-1.047*	0.516	0.335
	(0.582)	(0.538)	(0.468)	(0.432)	(0.595)	(0.546)	(0.552)	(0.723)	(0.606)	(0.562)	(0.556)	(0.554)
ΔFloor Space	-1.057***	-1.050***	-0.183	-0.197	-0.932***	-0.928***	-0.175	-0.227	-0.863***	-0.862***	-0.167	-0.192
	(0.251)	(0.248)	(0.193)	(0.197)	(0.232)	(0.235)	(0.190)	(0.201)	(0.227)	(0.232)	(0.190)	(0.194)
ΔREIT	0.326	0.232	0.660**	0.688**	0.207	0.159	0.560*	0.606	0.399	0.366	0.605*	0.603*
	(0.339)	(0.324)	(0.324)	(0.322)	(0.338)	(0.324)	(0.336)	(0.406)	(0.330)	(0.332)	(0.336)	(0.350)
ΔPopulation	-0.102	-0.105	-0.245	-0.248	-0.307**	-0.293**	-0.325	-0.262	-0.326**	-0.319**	-0.316	-0.284
	(0.138)	(0.137)	(0.202)	(0.199)	(0.143)	(0.143)	(0.214)	(0.220)	(0.141)	(0.143)	(0.215)	(0.208)
ΔResidential	0.217*	0.223**	0.512**	0.514***	0.244**	0.240**	0.525***	0.511***	0.218**	0.217**	0.519***	0.510***
	(0.112)	(0.109)	(0.100)	(0.099)	(0.109)	(0.105)	(0.095)	(0.124)	(0.110)	(0.107)	(0.096)	(0.102)
ΔClaims	0.085*	0.093**	0.075	0.070	0.125***	0.128***	0.092*	0.086	0.106**	0.109**	0.085*	0.083
	(0.046)	(0.045)	(0.047)	(0.048)	(0.047)	(0.047)	(0.050)	(0.057)	(0.048)	(0.048)	(0.050)	(0.051)
ΔSentiment					-0.469	-0.421	-0.250	-0.216	-0.226	-0.224	-0.211	-0.297
					(0.602)	(0.594)	(0.581)	(0.739)	(0.591)	(0.593)	(0.584)	(0.622)
U.S. CMBS Spread					0.065***	0.058***	0.026	0.021	0.059***	0.056***	0.023*	0.019
					(0.014)	(0.015)	(0.013)	(0.017)	(0.014)	(0.015)	(0.013)	(0.014)
TED Spread									-1.296**	-1.188*	-0.672	-0.217
									(0.652)	(0.710)	(0.527)	(0.561)
$\Delta\overline{GDP}$	0.061	-0.050	0.455*	0.424	-0.114	-0.178	0.330	0.330	0.127	0.078	0.408	0.318
	(0.278)	(0.280)	(0.274)	(0.266)	(0.279)	(0.279)	(0.297)	(0.346)	(0.289)	(0.315)	(0.306)	(0.319)
$\overline{StockReturns}$	0.180***	0.162***	0.102*	0.094*	0.174***	0.166***	0.101*	0.098*	0.147**	0.147***	0.088	0.095*
	(0.059)	(0.054)	(0.055)	(0.051)	(0.057)	(0.052)	(0.056)	(0.056)	(0.060)	(0.054)	(0.059)	(0.053)
Crisis Dummy	0.049**	0.043***	0.025	0.024	0.022	0.022	0.014	0.015	0.023	0.024	0.012	0.017
	(0.019)	(0.015)	(0.017)	(0.015)	(0.022)	(0.017)	(0.019)	(0.021)	(0.022)	(0.017)	(0.019)	(0.017)
ΔExchange Rate	-0.907	-0.723	-0.767	-0.820	-0.671	-0.575	-0.593	-0.686	-0.977*	-0.916*	-0.655	-0.673
	(0.568)	(0.541)	(0.553)	(0.553)	(0.552)	(0.528)	(0.573)	(0.683)	(0.545)	(0.543)	(0.573)	(0.598)
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	5.76***	4.56***	3.28***	2.04***	2.74***	2.02**	2.50**	1.64**	1.48	1.25	1.73*	1.07
Adj.-R^2	0.560	0.539	0.558	0.566	0.553	0.560	0.558	0.536	0.557	0.560	0.558	0.555

Table 4: Matching Financial and Non-Financial Center Office Markets

This table compares the results of the spatial models for office markets in *financial* and *non-financial centers.* Both subsamples are matched (*Matched*) based on the following covariates: city-level information on unemployment rate, construction activity, GDP growth per capita, as well as the short-term interest rate and a dummy variable as proxy for knowledge and technology hubs. Matching is based on a nearest-neighbor approach, allowing units from both groups to be discarded if outside the common support region. The *Full Sample* contains all non-financial centers for robustness, including Boston, Chicago, San Francisco, and Washington. We do not control for stock market integration when replicating the spatial models for non-financial centers as they do not host national stock exchange trading platforms. 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**			
	Matched		**Matched**		**Full Sample**	
	Turmoil	**Normal**	**Turmoil**	**Normal**	**Turmoil**	**Normal**
Spatial Lag	0.234*	-0.326	-0.128	-0.391	-0.112	0.060
	(0.120)	(0.951)	(0.173)	(1.038)	(0.182)	(0.152)
Stock Return	0.114**	0.122**	0.167**	0.216	0.066	0.064
	(0.052)	(0.061)	(0.067)	(0.139)	(0.048)	(0.048)
log(SRISK)	-0.001	0.001	-0.005*	-0.002	-0.003	-0.004
	(0.017)	(0.031)	(0.003)	(0.008)	(0.002)	(0.002)
ΔGDP Capita	1.020***	1.124***	1.283***	1.603***	1.102***	1.098***
	(0.173)	(0.217)	(0.218)	(0.486)	(0.179)	(0.178)
Term Spread	0.281	0.251	-1.290**	0.072	-1.107**	-1.054**
	(0.390)	(0.589)	(0.581)	(1.535)	(0.534)	(0.518)
ΔFloor Space	-1.364***	-1.535***	-1.675***	-1.822*	-0.893***	-0.905***
	(0.346)	(0.369)	(0.540)	(0.949)	(0.230)	(0.233)
ΔREIT	0.160	0.382	0.406	0.156	0.456	0.367
	(0.231)	(0.425)	(0.383)	(0.960)	(0.311)	(0.330)
ΔPopulation	0.042	0.052	1.443**	2.220	-0.304**	-0.296**
	(0.069)	(0.094)	(0.694)	(1.549)	(0.133)	(0.136)
ΔResidential	0.559***	0.586***	0.188*	0.331	0.158	0.168*
	(0.141)	(0.161)	(0.106)	(0.268)	(0.103)	(0.101)
ΔClaims	0.008	-0.016	0.197***	0.213*	0.087*	0.091*
	(0.046)	(0.079)	(0.054)	(0.126)	(0.049)	(0.049)
ΔSentiment	-0.006***	-0.006***	-0.742	-2.017	-0.036	-0.030
	(0.002)	(0.002)	(0.673)	(1.480)	(0.602)	(0.602)
Correlation to MSCI	0.084	0.086				
	(0.065)	(0.075)				
U.S. CMBS Spread	0.029	0.040	0.077***	0.116	0.056***	0.052***
	(0.022)	(0.092)	(0.021)	(0.078)	(0.015)	(0.017)
TED Spread	-3.237***	-4.697*	-1.565**	-0.738	-2.280***	-2.167***
	(0.984)	(2.662)	(0.701)	(2.433)	(0.611)	(0.724)
$\Delta\overline{GDP}$	0.558**	1.098	0.114	0.047	0.303	0.228
	(0.241)	(1.222)	(0.262)	(1.082)	(0.222)	(0.279)
$\Delta\overline{StockReturns}$	0.034	0.096	0.070	0.044	0.130**	0.116**
	(0.072)	(0.083)	(0.071)	(0.148)	(0.059)	(0.053)
Crisis Dummy	-0.029	-0.034	0.039*	0.007	0.032	0.028*
	(0.023)	(0.095)	(0.020)	(0.054)	(0.020)	(0.017)
ΔExchange Rate	-0.856**	-1.464	-1.380**	-1.162	-1.179**	-1.023*
	(0.403)	(0.948)	(0.582)	(1.462)	(0.509)	(0.531)
Observations	365	365	364	364	480	480
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Pesaran CD	3.76***	7.63***	1.97**	10.41***	1.60**	1.25
Adj.-R^2	0.621	0.608	0.597	0.496	0.533	0.536

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 (2010-2012) and the dotcom bubble burst (2000-2002), respectively. Model I computes the weighting matrix based on the interconnectedness of all financial centers in the sample. For the Sovereign Debt Crisis, Model II calculates the interconnectedness in the weighting matrix only based on the affected countries Greece, Ireland, Italy, Portgual, and Spain. For the dotcom bubble burst, Model II defines the interconnectedness in the weighting matrix only for countries with more extreme stock market declines than the MSCI world index-based downside risk of $\mu - \sigma = 0.03 - 0.27 = -0.24$. 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 2010-2012				**Dotcom Bubble Burst 2000-2002**			
	Model I		**Model II**		**Model I**		**Model II**	
	Office	**Retail**	**Office**	**Retail**	**Office**	**Retail**	**Office**	**Retail**
Spatial Lag	-0.288	0.029	-0.522	-0.361	0.498	0.324	0.638	0.111
	(0.257)	(0.212)	(0.470)	(0.266)	(0.491)	(0.427)	(0.393)	(0.310)
Stock Returns	0.084**	0.076*	0.081*	0.076*	0.080*	0.078*	0.077*	0.078*
	(0.043)	(0.044)	(0.042)	(0.044)	(0.042)	(0.044)	(0.042)	(0.044)
log(SRISK)	-0.011	-0.009	-0.016	-0.008	-0.011	-0.004	-0.011	-0.007
	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.012)	(0.011)	(0.012)
ΔGDP Capita	0.549***	0.800***	0.542***	0.808***	0.516***	0.814***	0.515***	0.805***
	(0.174)	(0.190)	(0.175)	(0.190)	(0.175)	(0.187)	(0.173)	(0.191)
Term Spread	0.064	1.068*	-0.157	1.113**	-0.019	0.934*	0.031	1.054*
	(0.473)	(0.563)	(0.448)	(0.545)	(0.448)	(0.556)	(0.446)	(0.554)
ΔFloor Space	-0.784***	0.049	-0.839***	0.058	-0.859***	0.037	-0.780***	0.052
	(0.295)	(0.164)	(0.282)	(0.165)	(0.280)	(0.162)	(0.285)	(0.167)
ΔREIT	0.220	-0.173	0.161	-0.170	0.153	-0.178	0.183	-0.177
	(0.220)	(0.285)	(0.215)	(0.282)	(0.214)	(0.289)	(0.216)	(0.285)
ΔPopulation	0.083	0.860	0.083	0.894	0.078	0.838	0.078	0.866
	(0.121)	(0.845)	(0.125)	(0.850)	(0.126)	(0.859)	(0.127)	(0.845)
ΔResidential	0.568***	0.475***	0.569***	0.472***	0.567***	0.476***	0.554***	0.477***
	(0.158)	(0.117)	(0.158)	(0.117)	(0.157)	(0.118)	(0.156)	(0.117)
ΔClaims	0.007	0.007	0.024	0.005	0.027	0.006	0.027	0.007
	(0.047)	(0.064)	(0.046)	(0.063)	(0.046)	(0.063)	(0.046)	(0.064)
ΔSentiment	-0.006***	0.000	-0.006***	0.000	-0.006***	0.000	-0.006***	0.000
	(0.047)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Correlation to MSCI	0.095	0.101	0.086	0.104*	0.079	0.109*	0.081	0.100
	(0.063)	(0.062)	(0.062)	(0.061)	(0.062)	(0.061)	(0.063)	(0.062)
U.S. CMBS Spread	0.084***	0.023	0.073***	0.027	0.063***	0.038	0.058***	0.027
	(0.021)	(0.019)	(0.016)	(0.016)	(0.017)	(0.025)	(0.017)	(0.018)
TED Spread	-3.311	-0.218	-3.018	-0.250	-2.889***	-0.024	-2.899***	-0.182
	(0.826)	(0.822)	(0.779)	(0.788)	(0.832)	(0.906)	(0.836)	(0.826)
$\Delta\overline{GDP}$	0.302	0.413	0.260	0.418	0.260	0.431*	0.279	0.414
	(0.198)	(0.253)	(0.194)	(0.254)	(0.199)	(0.258)	(0.201)	(0.255)
$\overline{StockReturns}$	0.175***	0.120**	0.157***	0.122**	0.162***	0.126**	0.167***	0.121**
	(0.055)	(0.051)	(0.054)	(0.050)	(0.055)	(0.052)	(0.055)	(0.051)
Crisis Dummy	0.026	-0.038*	0.008	-0.036*	0.017	-0.048**	0.021	-0.039**
	(0.021)	(0.021)	(0.018)	(0.018)	(0.017)	(0.019)	(0.018)	(0.018)
ΔExchange Rate	-0.270	0.045	-0.144	0.027	-0.095	0.036	-0.142	0.044
	(0.409)	(0.474)	(0.406)	(0.469)	(0.413)	(0.486)	(0.408)	(0.471)
Observations	464	368	464	368	464	368	464	368
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pesaran CD	6.37***	5.02***	7.10***	5.14***	7.87***	4.25***	7.94***	4.90***
Adj.-R^2	0.548	0.516	0.547	0.516	0.545	0.518	0.548	0.516

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 on the dummy variable for the financial crisis period, D_{Crisis}, the office market dummy, D_{Office}, and their interaction term. We use retail markets as the within-city counterfactual. 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. 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	0.096	0.209***	0.078	0.192***	0.114***	0.162***
	(0.123)	(0.041)	(0.089)	(0.029)	(0.016)	(0.043)
$D_{Crisis} \times D_{Office}$	-0.088**	-0.080**	0.001	-0.029	-0.057*	-0.065**
	(0.039)	(0.031)	(0.025)	(0.018)	(0.029)	(0.032)
D_{Crisis}	-0.150***		-0.040		-0.044**	
	(0.045)		(0.025)		(0.022)	
D_{Office}	0.007		-0.034*		-0.016	
	(0.022)		(0.018)		(0.018)	
Stock Returns	0.079*		0.108***			
	(0.042)		(0.036)			
log(SRISK)	0.000		0.004			
	(0.009)		(0.007)			
ΔGDP Capita	0.400		0.535**			
	(0.293)		(0.222)			
Term Spread	0.745		-0.051			
	(1.139)		(0.378)			
ΔFloor Space	0.094		-0.166		-0.060	
	(0.258)		(0.256)		(0.046)	
ΔREIT	-0.532*		-0.394			
	(0.320)		(0.240)			
ΔPopulation	-0.664		-0.103			
	(0.928)		(0.539)			
ΔResidential	0.490***		0.446***			
	(0.178)		(0.159)			
ΔClaims	0.109		0.049			
	(0.078)		(0.053)			
ΔSentiment	-0.003		-0.002			
	(0.003)		(0.003)			
ΔExchange Rate	1.065*		0.862*		1.048***	
	(0.635)		(0.461)		(0.072)	
GFC Turmoil			-0.193***			
			(0.031)			
Observations	265	265	424	424	355	424
City FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes
Adj.-R^2	0.644	0.583	0.612	0.544	0.465	0.108

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 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. 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. 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	0.105**	0.185***	0.103***	0.133***	0.098***	0.112***
	(0.052)	(0.066)	(0.038)	(0.036)	(0.010)	(0.042)
$D_{Crisis} \times D_{Center}$	-0.087**	-0.126***	-0.005	-0.011	-0.039	-0.019
	(0.034)	(0.039)	(0.023)	(0.024)	(0.033)	(0.027)
D_{Crisis}	-0.134***		-0.026		-0.066***	
	(0.037)		(0.020)		(0.018)	
D_{Center}	0.031		-0.005		-0.002	
	(0.022)		(0.018)		(0.015)	
Stock Returns	0.039		0.087***			
	(0.036)		(0.031)			
log(SRISK)	-0.003		-0.002			
	(0.004)		(0.003)			
ΔGDP Capita	0.897***		1.011***			
	(0.291)		(0.231)			
Term Spread	0.314		0.205			
	(1.318)		(0.428)			
ΔFloor Space	-0.823***		-0.832***		-0.125**	
	(0.233)		(0.212)		(0.053)	
ΔREIT	0.155		-0.211			
	(0.338)		(0.239)			
ΔPopulation	0.037		0.310			
	(0.946)		(0.492)			
ΔResidential	0.334*		0.288*			
	(0.197)		(0.162)			
ΔClaims	0.205***		0.134***			
	(0.068)		(0.049)			
ΔSentiment	-0.007***		-0.007***			
	(0.002)		(0.001)			
ΔExchange Rate	-0.347		0.303		0.917***	
	(0.685)		(0.490)		(0.083)	
GFC Turmoil			-0.154***			
			(0.027)			
Observations	275	275	440	440	290	440
City FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes
Adj.-R^2	0.678	0.539	0.648	0.531	0.329	0.097

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

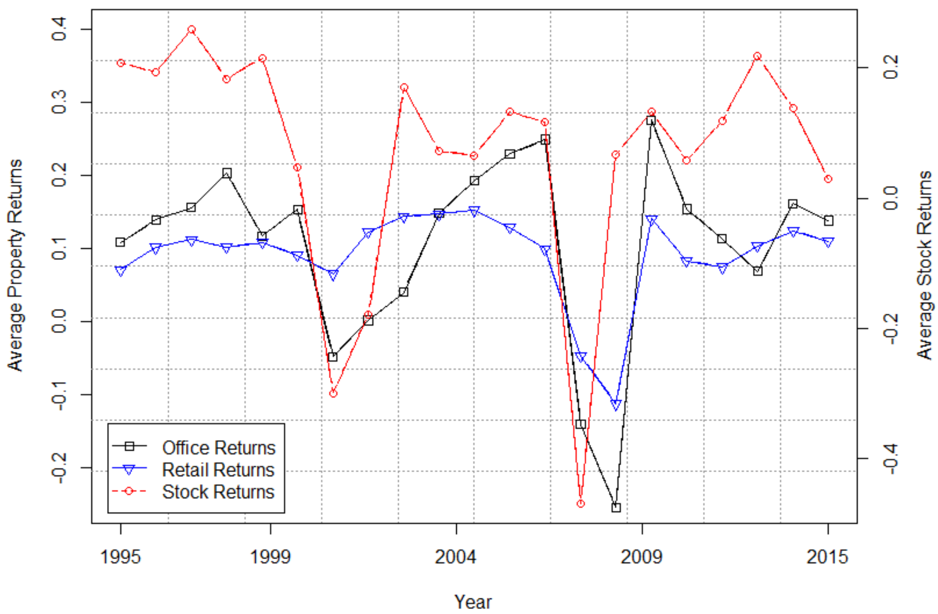
This table shows the effect of the total financial center-specific systemic risk on international office markets. Estimates are based on OLS. $SRISK_{high}$ and $SRISK_{low}$ capture office markets with the 25% highest and 25% lowest aggregated systemic risk per year. The *Financial Crisis* dummy is 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. $\times SRISK_{high} \times TechnologyCenter$ defines the interaction term between the Financial Crisis dummy, the dummy variable for being a Technology Center, and the variable $SRISK_{high}$. 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**	**Model VI**
Stock Returns	0.123***	0.121***	0.123***	0.124***	0.123***	0.125***
	(0.024)	(0.024)	(0.021)	(0.021)	(0.021)	(0.015)
log(SRISK)	-0.001					
	(0.001)					
ΔSRISK		-0.007				
		(0.004)				
ΔGDP Capita	0.840***	0.910***	0.843***	0.830***	0.844***	0.834***
	(0.197)	(0.228)	(0.179)	(0.179)	(0.180)	(0.067)
Term Spread	-0.633***	-0.578**	-0.746***	-0.777***	-0.745***	-0.809***
	(0.220)	(0.248)	(0.224)	(0.222)	(0.223)	(0.225)
ΔFloor Space	-0.739***	-0.809***	-0.780***	-0.762***	-0.780***	-0.740***
	(0.216)	(0.257)	(0.208)	(0.217)	(0.208)	(0.115)
ΔClaims	0.068**	0.084**	0.076***	0.070**	0.076***	0.066**
	(0.033)	(0.034)	(0.028)	(0.028)	(0.028)	(0.028)
ΔSentiment	-0.007***	-0.007***	-0.007***	-0.006***	-0.007***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔExchange Rate	0.017	-0.047	-0.003	-0.011	-0.003	0.011
	(0.269)	(0.320)	(0.237)	(0.238)	(0.239)	(0.089)
SRISK_{high}			-0.005	0.007	-0.005	0.002
			(0.008)	(0.011)	(0.008)	(0.010)
SRISK_{low}			0.001	0.001	0.001	
			(0.009)	(0.009)	(0.010)	
Technology Center						0.020**
						(0.009)
Financial Crisis	-0.143***	-0.137***	-0.139***	-0.119***	-0.139***	-0.119***
	(0.019)	(0.018)	(0.017)	(0.015)	(0.020)	(0.014)
$\times$ SRISK_{high}				-0.090**		-0.068**
				(0.045)		(0.031)
$\times$ SRISK_{low}					-0.002	
					(0.031)	
$\times$ $\text{SRISK}_{high} \times$ Technology Center						-0.061
						(0.045)
Observations	830	787	946	946	946	946
Adj.-R^2	0.509	0.517	0.509	0.514	0.508	0.517

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, which is based on the PMA sample availability. 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

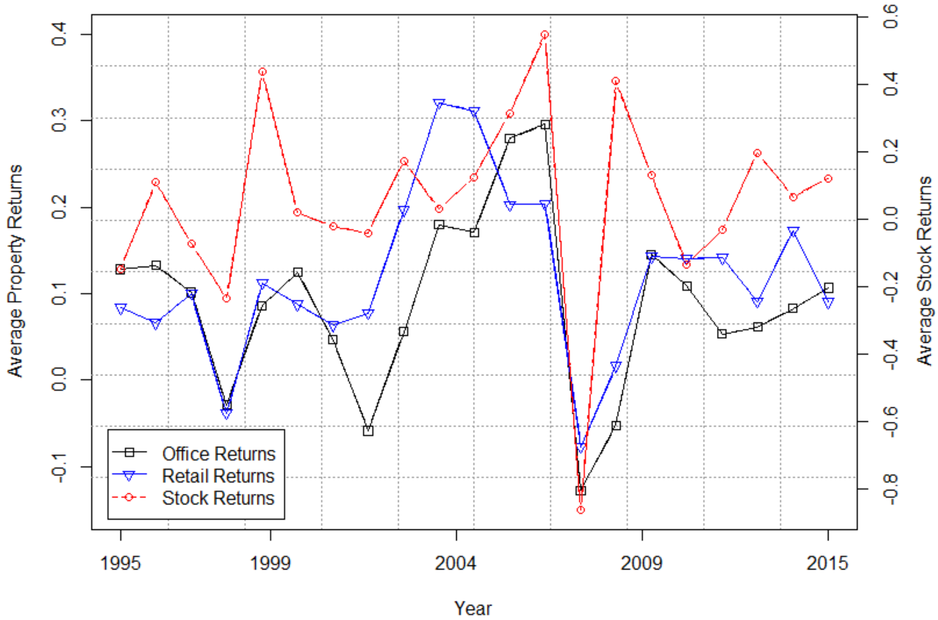


Figure 2: Impulse Response Function

This figure illustrates the impulse response functions and the corresponding 95% confidence intervals of a positive shock in stock (top) and office returns (bottom) on stock (left) and office returns (right), 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.

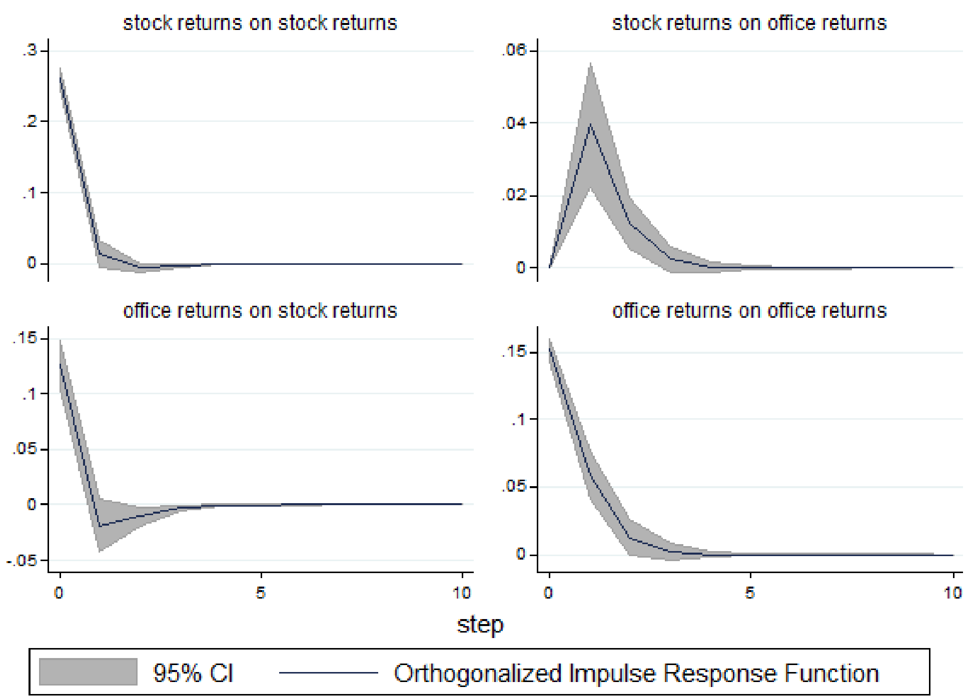


Figure 3: Financial Institutions in International Financial Centers

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.

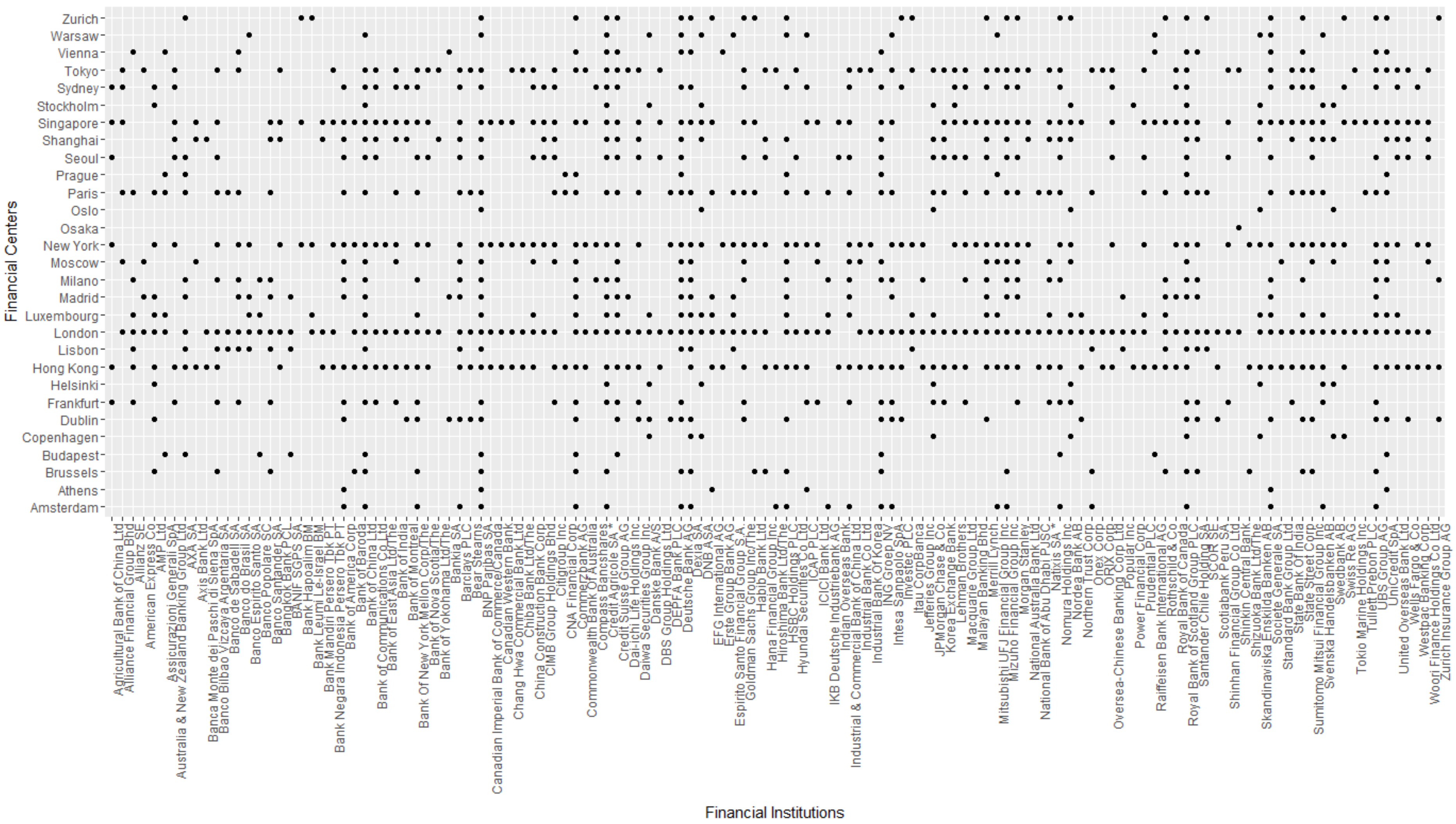
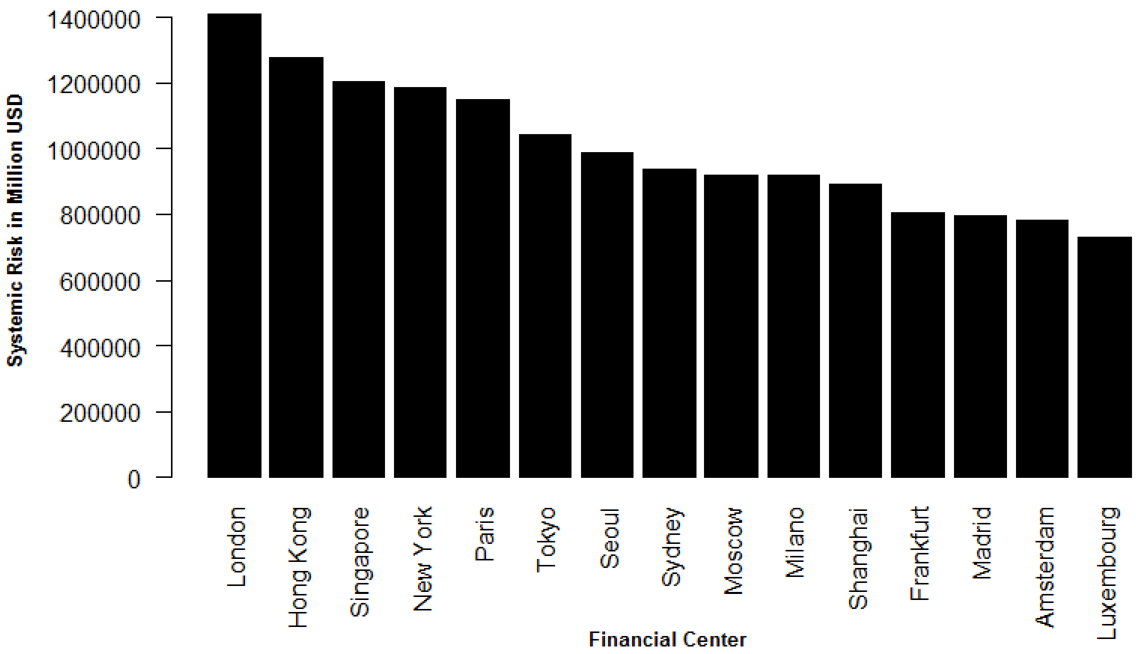


Figure 4: SRISK Ranking of Financial Centers

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

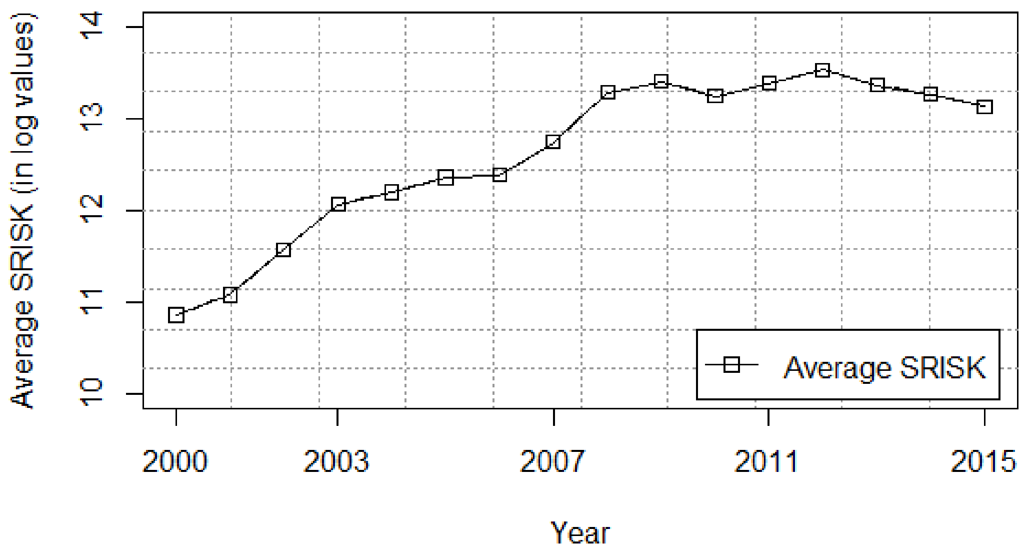


Figure 5: Average SRISK in Financial Centers versus Non-Financial Centers

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.

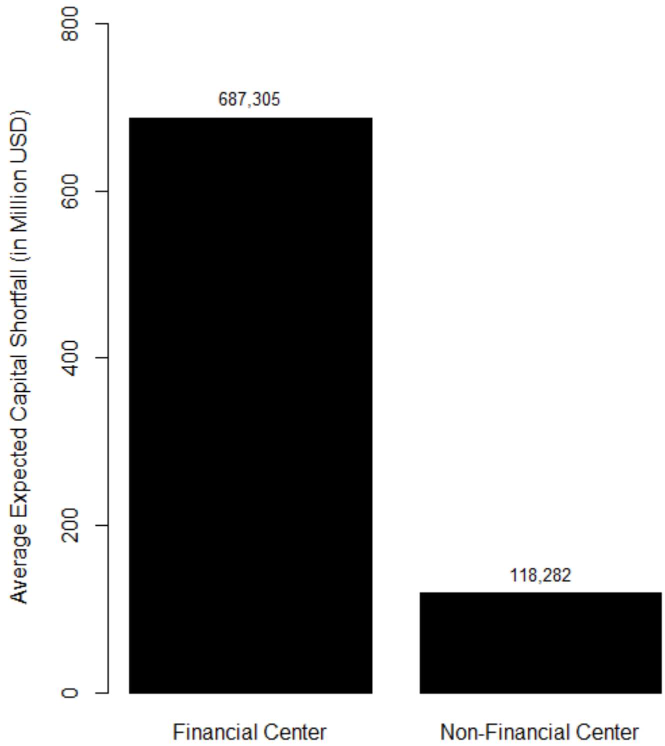
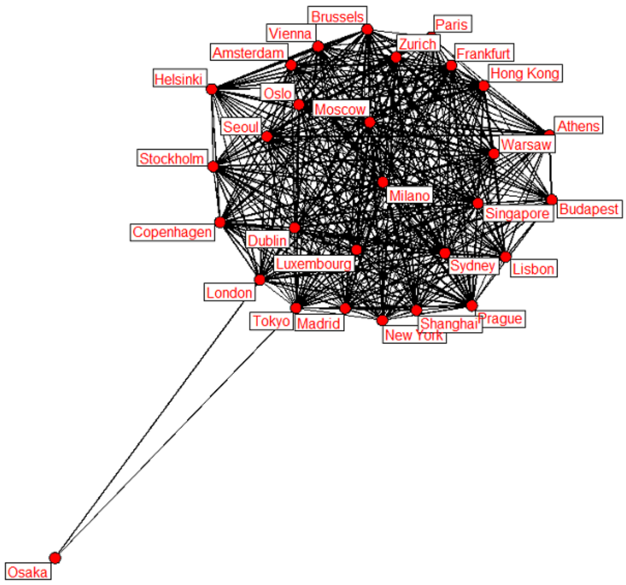


Figure 6: Interconnectedness of Financial and Non-Financial Centers

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

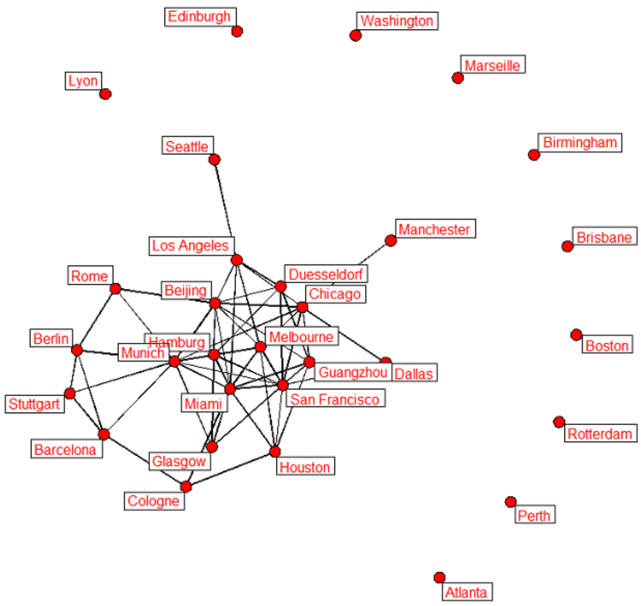
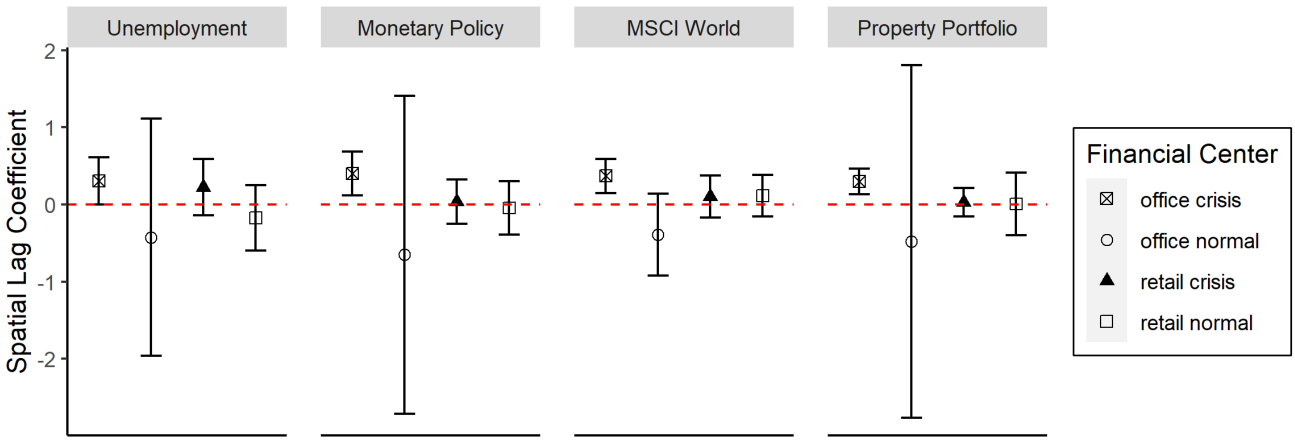


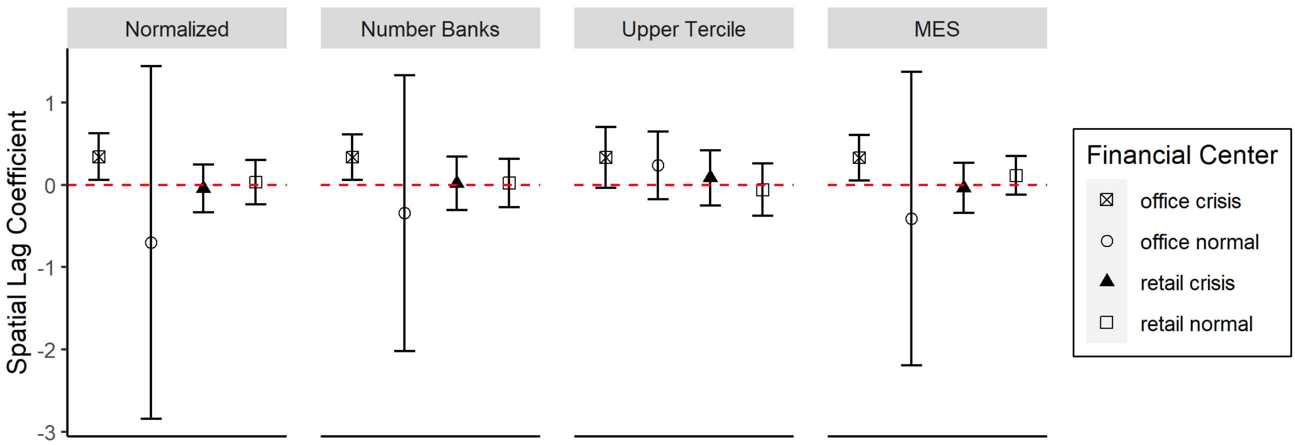
Figure 7: Additional Robustness Tests: Correlated Risk among Financial Centers

This figure shows the magnitude of the spatial lag coefficients and the corresponding 95% confidence bands for different model specifications. As *crisis* period, we use the financial crisis period 2007/2008. To measure spatial dependence during the crisis 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. Panel A replicates the results conditional on control variables as alternative channels: i) city-level unemployment rate, ii) conventional and unconventional monetary policy (defined as short-term interest rate level and central bank assets relative to GDP), iii) the MSCI world equity index returns, and iv) based on residuals conditional on the global property-specific market portfolio. Panel B replicates the results for different specifications of the weighting matrix: i) the spatial weights are divided by the number of common located banks (Normalized), ii) the spatial weights multiplied with the number of located banks, giving financial centers with a higher banking concentration a larger weight (Number Banks), iii) defining financial centers as the upper tercile of cities ranked according to the total SRISK (Upper Tercile), iv) using the Acharya, Pedersen, Philippon, and Richardson (2017) Marginal Expected Capital Shortfall as alternative systemic risk measure (MES).

Panel A: Conditional on Alternative Channels



Panel B: Different Specifications of Weighting Matrix



Internet Appendix for

Bank Systemic Risk Exposure and Office Market Interconnectedness

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September 2021

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: $G15$, $R30$

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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. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

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	17.959	-2.909***	-1.544	315
	(0.093)				
NCREIF NPI	-0.032	19.795	-2.408**	-1.491	315
	(0.077)				
Panel C: Correlation between PMA and NCREIF NPI Returns					
	Correlation	**Sector**	**Avg.Prop.**	**Min.Prop.**	**Max.Prop.**
Atlanta	0.83***	office	48.16	37	71
Boston	0.87***	office	20.07	11	48
Chicago	0.71***	office	58.38	43	76
Dallas	0.73***	office	52.70	41	63
Houston	0.73***	office	30.80	24	41
Los Angeles	0.94***	office	64.40	30	91
Miami	0.74***	office	20.68	13	36
New York	0.92***	office	52.10	30	80
San Francisco	0.80***	office	47.85	32	79
Seattle	0.89***	office	50.63	22	75
Washington	0.81***	office	128.20	70	162
Atlanta	0.60**	retail	40.76	18	58
Boston	0.67***	retail	10.67	5	25
Chicago	0.79***	retail	53.13	23	75
Dallas	0.62**	retail	25.21	12	37
Houston	0.40	retail	20.25	11	35
Los Angeles	0.78***	retail	31.82	15	61
Miami	0.78***	retail	14.78	5	27
New York	0.77***	retail	18.61	6	46
San Francisco	0.71***	retail	9.97	6	15
Washington	0.87***	retail	45.57	16	70

Table A.2: Commercial Real Estate Market Coverage

This table contains the market coverage of our sample. We show data availability and descriptive statistics 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

		Office				Retail					
City	**Country**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Trading Platform**	**Stock Index**
Amsterdam	Netherlands	0.04	0.07	-0.05	0.15	0.10	0.10	-0.14	0.33	Euronext	AEX
Athens	Greece	-0.01	0.13	-0.25	0.19	0.02	0.20	-0.40	0.42	Athen Stock Exchange	ATHEX Composite
Brussels	Belgium	0.04	0.05	-0.10	0.11	0.09	0.09	-0.09	0.26	Euronext	Bel20
Budapest	Hungary	0.03	0.10	-0.16	0.26	0.10	0.15	-0.28	0.32	Budapest Stock Exchange	BUX
Copenhagen	Denmark	0.04	0.07	-0.08	0.23	0.09	0.15	-0.24	0.36	OMX Nordic Exchange	OMXC20
Dublin	Ireland	0.07	0.30	-0.56	0.56	0.07	0.27	-0.70	0.38	Irish Stock Exchange	ISEQ
Frankfurt	Germany	0.03	0.13	-0.21	0.20	0.09	0.04	-0.01	0.15	Deutsche Börse	DAX30
Helsinki	Finland	0.04	0.08	-0.13	0.15	-	-	-	-	OMX Nordic Exchange	OMXH25
Hong Kong	Hong Kong	0.12	0.24	-0.39	0.59	0.17	0.27	-0.43	0.71	Hong Kong Stock Exchange	Hang Seng Index
Lisbon	Portugal	0.02	0.10	-0.17	0.18	0.06	0.11	-0.14	0.27	Euronext	PSI20
London	United Kingdom	0.08	0.20	-0.41	0.39	0.12	0.11	-0.07	0.35	London Stock Exchange	FTSE100
Luxembourg	Luxembourg	0.08	0.10	-0.13	0.23	-	-	-	-	Luxembourg Stock Exchange	LUX SE General
Madrid	Spain	0.04	0.21	-0.31	0.37	0.11	0.12	-0.21	0.31	BME Spanish Exchange	IBEX35
Milan	Italy	0.07	0.10	-0.08	0.27	0.12	0.15	-0.14	0.53	Borsa Italia	FTSE MIB
Moscow	Russia	0.14	0.33	-0.55	0.79	-	-	-	-	Moscow Exchange	MICEX Index
New York	USA	0.10	0.22	-0.52	0.39	0.09	0.07	-0.12	0.17	New York Stock Exchange	SNP500
Osaka	Japan	0.06	0.15	-0.24	0.22	0.15	0.23	-0.38	0.51	Japan Exchange Group	NIKKEI Futures
Oslo	Norway	0.09	0.17	-0.26	0.31	-	-	-	-	Oslo Bors	OBX
Paris	France	0.06	0.19	-0.27	0.49	0.10	0.13	-0.13	0.25	Euronext	CAC40
Prague	Czech Republic	0.06	0.09	-0.17	0.23	0.13	0.10	-0.07	0.30	Prague Stock Exchange	PX50
Seoul	South Korea	0.10	0.10	-0.15	0.26	0.16	0.08	0.06	0.30	Korea Exchange	KOSPI
Shanghai	China	0.08	0.11	-0.15	0.21	0.10	0.08	-0.03	0.21	Shanghai Stock Exchange	SE A SPI
Singapore	Singapore	0.06	0.29	-0.38	0.71	0.06	0.09	-0.12	0.18	Singapore Exchange	Straits Time Index
Stockholm	Sweden	0.05	0.14	-0.22	0.24	0.08	0.10	-0.14	0.26	OMX Nordic Exchange	OMXS30
Sydney	Australia	0.08	0.11	-0.12	0.25	0.09	0.10	-0.14	0.26	Australian Sec. Exchange	ASX
Tokyo	Japan	0.06	0.20	-0.35	0.35	0.20	0.29	-0.29	0.61	Japan Exchange Group	NIKKEI25
Vienna	Austria	0.04	0.05	-0.05	0.12	0.08	0.09	-0.10	0.333	Wiener Börse	ATX
Warsaw	Poland	0.07	0.14	-0.23	0.35	0.14	0.10	-0.06	0.30	Warsaw Stock Exchange	WIG
Zurich	Switzerland	0.04	0.12	-0.13	0.29	-	-	-	-	SIX Swiss Exchange	SSMI

Table A.2 continued.

Panel B: Non-financial Centers

		Office				Retail			
City	**Country**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Atlanta	USA	0.08	0.12	-0.16	0.23	0.08	0.07	-0.09	0.14
Barcelona	Spain	0.03	0.16	-0.33	0.30	0.11	0.13	-0.21	0.34
Beijing	China	0.10	0.13	-0.02	0.43	0.14	0.15	-0.17	0.40
Berlin	Germany	0.03	0.10	-0.12	0.19	0.08	0.08	-0.11	0.18
Birmingham	United Kingdom	0.07	0.12	-0.23	0.21	0.05	0.10	-0.17	0.21
Boston	USA	0.08	0.19	-0.37	0.35	0.09	0.07	-0.11	0.20
Brisbane	Australia	0.09	0.16	-0.28	0.41	-	-	-	-
Chicago	USA	0.07	0.12	-0.16	0.37	0.08	0.07	-0.09	0.17
Cologne	Germany	0.05	0.07	-0.05	0.20	0.07	0.04	-0.00	0.14
Dallas	USA	0.08	0.12	-0.16	0.24	0.08	0.07	-0.10	0.15
Dusseldorf	Germany	0.04	0.08	-0.12	0.19	-	-	-	-
Edinburgh	United Kingdom	0.06	0.13	-0.21	0.27	-	-	-	-
Glasgow	United Kingdom	0.08	0.12	-0.18	0.32	0.05	0.11	-0.22	0.23
Guangzhou	China	0.11	0.10	0.00	0.27	0.13	0.15	0.02	0.46
Hamburg	Germany	0.04	0.09	-0.19	0.16	0.08	0.04	-0.01	0.16
Houston	USA	0.10	0.16	-0.20	0.49	0.08	0.06	-0.11	0.16
Lille	France	0.09	0.07	-0.04	0.25	0.11	0.11	-0.14	0.31
Los Angeles	USA	0.09	0.17	-0.36	0.31	0.10	0.09	-0.15	0.19
Lyon	France	0.08	0.06	-0.04	0.17	0.12	0.13	-0.14	0.43
Manchester	United Kingdom	0.08	0.13	-0.21	0.24	0.04	0.12	-0.24	0.23
Marseille	France	0.09	0.08	-0.06	0.25	0.11	0.16	-0.13	0.60
Melbourne	Australia	0.09	0.09	-0.09	0.23	0.10	0.09	-0.07	0.31
Miami	USA	0.09	0.12	-0.21	0.27	0.09	0.09	-0.14	0.53
Munich	Germany	0.06	0.12	-0.16	0.24	0.09	0.06	0.03	0.29
Nagoya	Japan	0.05	0.14	-0.20	0.27	0.13	0.20	-0.16	0.51
Perth	Australia	0.13	0.22	-0.20	0.65	-	-	-	-
Rome	Italy	0.05	0.08	-0.07	0.24	0.12	0.15	-0.08	0.53
Rotterdam	Netherlands	0.05	0.06	-0.06	0.13	-	-	-	-
San Francisco	USA	0.10	0.30	-0.44	0.45	0.10	0.08	-0.17	0.19
Seattle	USA	0.07	0.18	-0.38	0.30	-	-	-	-
Stuttgart	Germany	0.05	0.06	-0.06	0.12	-	-	-	-
Washington	USA	0.09	0.11	-0.14	0.28	0.09	0.09	-0.16	0.17

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
ΔGDP 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
ΔFloor 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)
ΔREIT	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
ΔPopulation	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
ΔResidential	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
ΔClaims	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)
ΔSentiment	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.

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
ΔExchange Rate	We compute log-changes of nominal exchange rates for all countries relative to the U.S. dollar.	Thomson Reuters Datastream
MSCI World	We use the MSCI World equity index as proxy for the global stock market portfolio. Returns are calculated as log-differences.	Thomson Reuters Datastream
Unemployment	We collect city-level unemployment rates (relative to overall population) from various data sources from 2001 to 2015. UK data was collected from the Bureau of Labor Statistics. For the following countries, only national Eurostat data is available: Denmark, Ireland, Netherlands, Poland, Finland, Sweden.	OECD, Eurostat, Bureau of Labor Statistics
MES	As alternative systemic risk measure we use the Marginal Expected Capitel Shortfall (MES), as proposed by Acharya, Pedersen, Philippon, and Richardson (2017).	NYU Stern V-Lab, Own Calculation
Central Bank Assets	As proxy for unconventional monetary policy, we use central bank assets as a share of GDP. Assets contain claims on domestic non-financial sector, such as central and local governments.	Worldbank
ΔGDP Capita$_{city}$	We also collect city-level GDP growth per capita from 2001 to 2015.	OECD
Technology Center	As proxy for technology centers (or innovation centers), we specify a dummy variable, which is equal to 1 if the city is located in near distance to a top university. As proxy for top universities, we use Top 50 University locations since 2010 from the Times Higher Education World Index Ranking.	Times Higher Education

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
ΔFloor Space Office	0.03	0.04	-0.04	0.42	973
ΔFloor 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
ΔPopulation	0.01	0.03	-0.66	0.18	972
Country-Level	**Mean**	**Std.Dev.**	**Min.**	**Max.**	**Obs.**
ΔGDP capita	0.04	0.10	-0.26	0.41	448
Term Spread	0.01	0.02	-0.07	0.22	448
ΔREITs	0.00	0.05	-0.29	0.13	448
ΔResidential	0.04	0.07	-0.23	0.39	448
ΔExchange Rate	0.00	0.09	-0.46	0.19	448
ΔClaims	0.08	0.18	-0.49	0.67	448
ΔSentiment	-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 and the corresponding p-values. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	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)	1.00														
ΔGDP Capita	0.02	1.00													
Stock Returns	0.00	-0.03	1.00												
Term Spread	-0.03	-0.21***	0.02	1.00											
ΔFloor Space	0.05	0.31***	0.01	-0.30***	1.00										
ΔREITs	0.00	0.51***	-0.08**	-0.03	0.09***	1.00									
ΔPopulation	0.07**	0.19***	0.06*	-0.13***	0.29***	0.00	1.00								
ΔResidential	-0.09**	0.28***	0.11***	-0.29***	0.16***	0.15***	0.12***	1.00							
ΔClaims	-0.05	0.41***	0.23***	-0.21***	0.23***	0.15***	0.04	0.37***	1.00						
ΔSentiment	-0.02	-0.02	-0.02	0.01	0.01	-0.01	0.00	-0.07**	-0.04	1.00					
Correlation	0.31***	-0.19***	-0.13***	0.13***	-0.37***	-0.03	-0.04	-0.08*	-0.18***	0.00	1.00				
ΔExchange Rate	0.01	0.78***	-0.10***	-0.03	0.04	0.63***	0.02	0.14***	0.33***	0.00	-0.02	1.00			
MSCI World Returns	0.00	0.22***	0.14***	-0.03	-0.08***	-0.05	-0.00	0.17***	0.05	-0.05	-0.01	0.10	1.00		
U.S. CMBS Spread	0.02	0.06*	-0.15***	0.08**	-0.08**	0.00	0.00	-0.09***	-0.12***	-0.04	0.13***	0.04	0.31***	1.00	
TED Spread	-0.06*	-0.01	-0.31***	0.04	0.03	-0.03	0.00	-0.16***	-0.12***	0.01	-0.15***	0.03	-0.34***	-0.02	1.00

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**	0.185**	-0.071	-0.049
	(0.081)	(0.093)	(0.077)	(0.079)
TED Spread	-12.084	-12.589	-8.050	-12.169
	(14.156)	(14.143)	(14.433)	(14.229)
ΔMSCI World	-0.281	-0.307	-0.205	0.036
	(0.280)	(0.282)	(0.285)	(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 without Crisis Dummy

This table shows the results of spatial models for office and retail markets in financial centers from 2001 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			
	Office		**Retail**	
	Turmoil	**Normal**	**Turmoil**	**Normal**
Spatial Lag	0.221**	-0.374	-0.164	0.158
	(0.110)	(0.614)	(0.126)	(0.104)
Stock Returns	0.083*	0.089*	0.078*	0.081*
	(0.043)	(0.049)	(0.044)	(0.044)
log(SRISK)	-0.013	-0.015	-0.005	-0.006
	(0.010)	(0.010)	(0.010)	(0.010)
ΔGDP Capita	0.515***	0.568***	0.803***	0.783***
	(0.176)	(0.183)	(0.190)	(0.186)
Term Spread	0.074	0.039	0.908	0.867
	(0.454)	(0.532)	(0.562)	(0.562)
ΔFloor Space	-0.800***	-0.908***	0.031	0.028
	(0.285)	(0.290)	(0.164)	(0.161)
ΔREIT	0.188	0.385	-0.144	-0.163
	(0.215)	(0.307)	(0.284)	(0.278)
ΔPopulation	0.092	0.108	0.863	0.751
	(0.120)	(0.141)	(0.864)	(0.862)
ΔResidential	0.568***	0.605***	0.461***	0.461***
	(0.156)	(0.163)	(0.120)	(0.120)
ΔClaims	0.009	-0.011	0.012	0.010
	(0.046)	(0.058)	(0.064)	(0.062)
ΔSentiment	-0.006***	-0.006***	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Correlation to MSCI	0.060	0.061	0.071	0.085
	(0.060)	(0.093)	(0.056)	(0.055)
U.S. CMBS Spread	0.068***	0.093**	0.016	0.012
	(0.015)	(0.041)	(0.015)	(0.014)
TED Spread	-3.073***	-4.372***	-0.181	-0.030
	(0.778)	(1.558)	(0.807)	(0.808)
$\Delta\overline{GDP}$	0.293	0.839	0.355	0.197
	(0.191)	(0.696)	(0.252)	(0.258)
$\Delta\overline{StockReturns}$	0.097*	0.167***	0.181***	0.137***
	(0.053)	(0.064)	(0.051)	(0.048)
ΔExchange Rate	-0.157	-0.660	-0.029	0.029
	(0.402)	(0.577)	(0.470)	(0.460)
Observations	464	464	368	368
Fixed Effects	Yes	Yes	Yes	Yes
Pesaran CD	6.27***	12.33***	5.17***	3.45***
Adj.-R^2	0.549	0.536	0.516	0.522

Table A.9: Correlated Risk Conditional on Employment Channel

This table shows the results of spatial models for office and retail markets in financial centers from 2001 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			
	Office		**Retail**	
	Turmoil	**Normal**	**Turmoil**	**Normal**
Spatial Lag	0.306*	-0.425	0.224	-0.175
	(0.158)	(0.786)	(0.185)	(0.217)
Stock Return	0.058	0.059	0.105**	0.103*
	(0.051)	(0.057)	(0.051)	(0.053)
log(SRISK)	-0.026**	-0.033*	-0.023*	-0.023
	(0.013)	(0.019)	(0.014)	(0.015)
Unemployment	0.830**	0.956**	-0.012	0.015
	(0.391)	(0.402)	(0.416)	(0.418)
ΔGDP Capita	0.530***	0.635***	0.639***	0.675***
	(0.188)	(0.203)	(0.201)	(0.207)
Term Spread	-0.276	-0.373	1.592*	1.591*
	(0.702)	(0.854)	(0.826)	(0.850)
ΔFloor Space	-0.931**	-1.106***	0.207	0.206
	(0.419)	(0.422)	(0.201)	(0.204)
ΔREIT	0.209	0.448	-0.217	-0.181
	(0.228)	(0.387)	(0.329)	(0.333)
ΔPopulation	2.535**	2.905**	0.915	1.035
	(1.252)	(1.347)	(1.376)	(1.380)
ΔResidential	0.547***	0.587***	0.293*	0.295*
	(0.189)	(0.196)	(0.151)	(0.153)
ΔClaims	0.072	0.056	0.002	0.005
	(0.054)	(0.070)	(0.082)	(0.085)
ΔSentiment	-0.006***	-0.006***	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Correlation to MSCI	0.126*	0.143*	0.137*	0.122
	(0.067)	(0.076)	(0.076)	(0.077)
U.S. CMBS Spread	0.079***	0.110*	0.014	0.015
	(0.018)	(0.064)	(0.017)	(0.018)
TED Spread	-3.994***	-5.687*	-1.720**	-1.922**
	(0.941)	(2.222)	(0.857)	(0.963)
$\Delta\overline{GDP}$	0.440*	1.058	0.733***	0.918**
	(0.230)	(1.122)	(0.279)	(0.374)
$\Delta\overline{StockReturns}$	0.063	0.163**	-0.008	0.042
	(0.081)	(0.072)	(0.070)	(0.064)
Crisis Dummy	-0.018	-0.011	-0.061**	-0.059*
	(0.031)	(0.071)	(0.027)	(0.031)
ΔExchange Rate	-0.269	-0.916	-0.036	-0.153
	(0.421)	(0.770)	(0.570)	(0.574)
Observations	330	330	255	255
Fixed Effects	Yes	Yes	Yes	Yes
Pesaran CD	3.94***	9.21***	0.69	1.73*
Adj.-R^2	0.565	0.547	0.460	0.454

Table A.10: Correlated Risk Conditional Funding Liquidity Channel

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 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			
	Office		**Retail**	
	Turmoil	**Normal**	**Turmoil**	**Normal**
Spatial Lag	0.403***	-0.653	0.037	-0.046
	(0.145)	(1.050)	(0.148)	(0.176)
Stock Returns	0.081*	0.092*	0.072*	0.072*
	(0.043)	(0.050)	(0.043)	(0.043)
log(SRISK)	-0.024**	-0.028*	-0.024**	-0.024**
	(0.011)	(0.017)	(0.011)	(0.012)
ΔGDP Capita	0.625***	0.746***	0.806***	0.810***
	(0.165)	(0.196)	(0.183)	(0.184)
Short-term Interest	-1.406**	-1.680	-1.933***	-1.979***
	(0.623)	(1.199)	(0.552)	(0.591)
Central Bank Assets	-0.161*	-0.188*	-0.115	-0.114
	(0.093)	(0.106)	(0.149)	(0.150)
ΔFloor Space	-0.576*	-0.723**	0.089	0.089
	(0.315)	(0.336)	(0.165)	(0.165)
ΔREIT	0.229	0.577	-0.197	-0.192
	(0.211)	(0.402)	(0.261)	(0.261)
ΔPopulation	0.067	0.085	0.040	0.046
	(0.082)	(0.104)	(0.851)	(0.856)
ΔResidential	0.545***	0.610***	0.429***	0.428***
	(0.135)	(0.138)	(0.105)	(0.105)
ΔClaims	0.027	0.001	0.040	0.042
	(0.046)	(0.064)	(0.060)	(0.061)
ΔSentiment	-0.006***	-0.006***	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Correlation to MSCI	0.077	0.092	0.116*	0.113*
	(0.061)	(0.075)	(0.062)	(0.062)
U.S. CMBS Spread	0.072***	0.118	0.024*	0.025
	(0.015)	(0.090)	(0.015)	(0.016)
TED Spread	-3.487***	-5.818**	-0.432	-0.475
	(0.785)	(2.432)	(0.852)	(0.890)
$\Delta\overline{GDP}$	0.391**	1.363	0.434*	0.485
	(0.196)	(1.404)	(0.240)	(0.315)
$\Delta\overline{StockReturns}$	-0.010	0.102	0.091	0.099**
	(0.067)	(0.066)	(0.058)	(0.050)
Crisis Dummy	-0.036	-0.043	-0.033*	-0.034
	(0.023)	(0.090)	(0.020)	(0.023)
ΔExchange Rate	-0.283	-1.187	0.097	0.081
	(0.389)	(0.810)	(0.435)	(0.434)
Observations	464	464	368	368
Fixed Effects	Yes	Yes	Yes	Yes
Pesaran CD	5.30***	16.13***	2.81***	3.24***
Adj.-R^2	0.559	0.532	0.530	0.528

Table A.11: Correlated Risk Conditional on MSCI World Index

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 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			
	Office		**Retail**	
	Turmoil	**Normal**	**Turmoil**	**Normal**
Spatial Lag	0.369***	-0.390	0.103	0.112
	(0.112)	(0.271)	(0.138)	(0.138)
Stock Return	0.090**	0.154***	0.124***	0.143***
	(0.037)	(0.033)	(0.042)	(0.039)
log(SRISK)	-0.027***	-0.033***	-0.015	-0.013
	(0.010)	(0.011)	(0.011)	(0.011)
ΔGDP Capita	0.354**	0.326*	0.629***	0.632***
	(0.164)	(0.173)	(0.177)	(0.177)
Term Spread	0.113	0.117	1.380**	1.120*
	(0.385)	(0.410)	(0.559)	(0.577)
ΔFloor Space	-0.638**	-0.775***	0.041	0.010
	(0.279)	(0.283)	(0.170)	(0.165)
ΔREIT	-0.219	-0.178	-0.342	-0.328
	(0.218)	(0.223)	(0.290)	(0.285)
ΔPopulation	0.073	0.078	0.661	0.587
	(0.081)	(0.084)	(0.857)	(0.869)
ΔResidential	0.517***	0.542***	0.472***	0.460***
	(0.142)	(0.146)	(0.115)	(0.117)
ΔClaims	0.051	0.071	0.040	0.046
	(0.046)	(0.051)	(0.066)	(0.064)
ΔSentiment	-0.006***	-0.006***	0.001	0.0004
	(0.002)	(0.002)	(0.001)	(0.001)
Correlation to MSCI	0.110*	0.128*	0.126**	0.139**
	(0.061)	(0.071)	(0.062)	(0.061)
U.S. CMBS Spread	0.052***	0.070***	0.010	0.006
	(0.015)	(0.021)	(0.016)	(0.015)
TED Spread	-1.235	-2.166***	0.282	0.366
	(0.798)	(0.826)	(0.859)	(0.862)
$\Delta\overline{GDP}$	-0.270	0.127	0.210	0.138
	(0.223)	(0.286)	(0.276)	(0.288)
ΔMSCI World	0.197***	0.272***	0.102**	0.090**
	(0.038)	(0.074)	(0.040)	(0.044)
Crisis Dummy	-0.046***	-0.049*	-0.059***	-0.040*
	(0.017)	(0.027)	(0.019)	(0.021)
ΔExchange Rate	0.880**	0.718	0.546	0.478
	(0.439)	(0.452)	(0.509)	(0.495)
Observations	464	464	368	368
Fixed Effects	Yes	Yes	Yes	Yes
Pesaran CD	6.56***	11.66***	4.74***	3.91***
Adj.-R^2	0.577	0.563	0.519	0.524

Table A.12: Correlated Risk Conditional on Global Property Market Portfolio

This table shows the results of spatial models for office and retail markets in financial centers from 2000 to 2015. 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). 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			
	Office		**Retail**	
	Turmoil	**Normal**	**Turmoil**	**Normal**
Spatial Lag	0.296***	-0.479	0.028	0.007
	(0.084)	(1.166)	(0.095)	(0.207)
Stock Returns	0.095*	0.110	0.072	0.075
	(0.053)	(0.075)	(0.054)	(0.054)
log(SRISK)	-0.023*	-0.020	-0.010	-0.009
	(0.012)	(0.019)	(0.012)	(0.014)
ΔGDP Capita	0.622***	0.821***	0.955***	0.955***
	(0.218)	(0.265)	(0.236)	(0.237)
Term Spread	0.345	0.144	1.322**	1.252*
	(0.595)	(1.068)	(0.635)	(0.754)
ΔFloor Space	-1.076***	-1.337***	0.015	0.003
	(0.323)	(0.371)	(0.200)	(0.200)
ΔREIT	0.743**	1.377	0.081	0.083
	(0.289)	(1.034)	(0.371)	(0.379)
ΔPopulation	0.126	0.147	1.701*	1.655*
	(0.177)	(0.225)	(0.974)	(0.978)
ΔResidential	0.702***	0.809***	0.549***	0.544***
	(0.179)	(0.245)	(0.137)	(0.141)
Correlation to MSCI	0.072	0.087	0.026	0.027
	(0.078)	(0.101)	(0.073)	(0.073)
ΔClaims	-0.028	-0.089	-0.009	-0.004
	(0.052)	(0.134)	(0.069)	(0.071)
ΔSentiment	-0.006***	-0.006***	0.0001	0.0001
	(0.002)	(0.002)	(0.001)	(0.001)
U.S. CMBS Spread	0.149***	0.200	0.045**	0.043*
	(0.018)	(0.195)	(0.018)	(0.024)
TED Spread	-6.287***	-9.500*	-1.746*	-1.660
	(0.927)	(5.614)	(0.898)	(1.096)
$\Delta\overline{GDP}$	1.714***	3.060	1.662***	1.650***
	(0.232)	(2.561)	(0.307)	(0.462)
$\Delta\overline{StockReturns}$	0.296***	0.365***	0.310***	0.321***
	(0.071)	(0.094)	(0.076)	(0.062)
Crisis Dummy	-0.027	-0.053	-0.049*	-0.042
	(0.025)	(0.214)	(0.026)	(0.044)
ΔExchange Rate	-2.443***	-4.029*	-1.709***	-1.723***
	(0.530)	(1.139)	(0.618)	(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

Table A.13: 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)
ΔGDP 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)
ΔFloor 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)
ΔREIT	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)
ΔPopulation	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)
ΔResidential	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)
ΔClaims	-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)
ΔSentiment	-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)
ΔExchange 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.14: Mean Comparison of Control Variables (Treated vs Control Group)

This table shows the average values and the corresponding t-test mean difference between financial (treated) and non-financial centers (control group). Panel A shows the mean comparison for all data before the matching approach. Panel B shows the mean comparison after the matching. Matching is based on a nearest-neighbor approach using the estimated propensity scores from a probit regression. As control variables, we use city-level information on population growth, construction activity, per capita GDP growth, and a dummy variable (Top University) equal to 1 if a top university is located in close proximity to the financial center. We also use the short-term interest rate to capture the homogeneity within countries and monetary policy unions. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

Panel A: All Data

	Treated (FC)	**Control (NFC)**	Δ t-test
ΔPopulation	0.007	0.010	1.183
Construction	0.022	0.013	-5.007***
ΔGDP Capita$_{city}$	0.015	0.009	-2.325**
Top University	0.193	0.308	3.622***
Short-Term Interest	0.023	0.022	-0.245

Panel B: Matched Data

	Treated (FC)	**Control (NFC)**	Δ t-test
ΔPopulation	0.010	0.010	-0.188
Construction	0.016	0.014	-1.994**
ΔGDP Capita$_{city}$	0.012	0.011	-0.342
Top University	0.206	0.260	1.646
Short-Term Interest	0.021	0.022	0.305

Table A.15: Robustness Tests for Different Spatial Weights

This table shows the results of the estimated spatial lag coefficient from Model III for office and retail markets in 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. We replicate the model for different specifications of the weighting matrix. Panel A divides the spatial weights by the total number of common located banks L to normalize by the banking concentration in financial centers. Panel B multiplies the spatial weight by the total number of common located banks L to give financial centers with a higher bank concentration a larger weight. Panel C uses the established spatial weights but defines financial centers as the upper tercile of cities ranked according to the average SRISK. Panel D computes the spatial weight as sum of the common located financial companies' marginal expected shortfall (MES) measure of Acharya, Pedersen, Philippon, and Richardson (2017). Panel E gives a larger weight to linkages between multi-functional centers (using the definition of technology center TC if a top university is located in close proximity to the financial center). In a first step, we compute the established spatial weights. In a second step, we replace the row-normalized weight by a maximum value of 1 if financial centers i or j are defined as technology center (TC). 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 the 1%, 5%, and 10% level, respectively.

	FC Office		**FC Retail**	
	Turmoil	**Normal**	**Turmoil**	**Normal**
Panel A: Normalized by Number of Banks				
$\mathbf{w}_{ij,t} = (\sum_l \mathbb{1}\left(main\ office_{il} \cap main\ office_{jl}\right) \times \%SRISK_{l,t})/L$				
Spatial Lag	0.341**	-0.700	-0.044	0.032
	(0.146)	(1.104)	(0.149)	(0.139)
Pesaran CD	6.16***	17.17***	5.06***	4.65***
Adj.-R^2	0.550	0.523	0.517	0.518
Panel B: Weighted by Number of Banks				
$\mathbf{w}_{ij,t} = (\sum_l \mathbb{1}\left(main\ office_{il} \cap main\ office_{jl}\right) \times \%SRISK_{l,t}) \times L$				
Spatial Lag	0.335**	-0.345	0.018	0.019
	(0.144)	(0.863)	(0.168)	(0.152)
Pesaran CD	6.24***	12.35***	5.04***	4.86***
Adj.-R^2	0.547	0.533	0.516	0.517
Panel C: Financial Centers as Upper SRISK Tercile				
$\mathbf{w}_{ij,t} = \sum_l \mathbb{1}\left(main\ office_{il} \cap main\ office_{jl}\right) \times \%SRISK_{l,t}$				
Spatial Lag	0.332*	0.236	0.085	-0.060
	(0.193)	(0.212)	(0.173)	(0.163)
Pesaran CD	1.81*	2.24***	1.53	1.96*
Adj.-R^2	0.526	0.524	0.480	0.489
Panel D: Weighting based on MES				
$\mathbf{w}_{ij,t} = \sum_l MES_{i,j,l}$				
Spatial Lag	0.329**	-0.409	-0.036	0.113
	(0.143)	(0.919)	(0.156)	(0.120)
Pesaran CD	6.10***	12.90***	4.18***	3.16***
Adj.-R^2	0.546	0.529	0.518	0.523
Panel E: Maximum Weights to Technology Centers				
Step 1: $w_{ij,t} = \sum_l \mathbb{1}\left(main\ office_{il} \cap main\ office_{jl}\right) \times \%SRISK_{l,t}$				
Step 2: $w^*_{ij} = \begin{cases} w_{ij}/\sum_j w_{ij} & ,i,j \notin TC \\ 1 & ,i,j \in TC \end{cases}$				
Spatial Lag	0.301**	-0.523	0.024	-0.088
	(0.151)	(0.970)	(0.158)	(0.220)
Pesaran CD	6.10***	15.36***	5.04***	6.28***
Adj.-R^2	0.549	0.527	0.515	0.513

Table A.16: Difference-in-Difference Model: Placebo Test

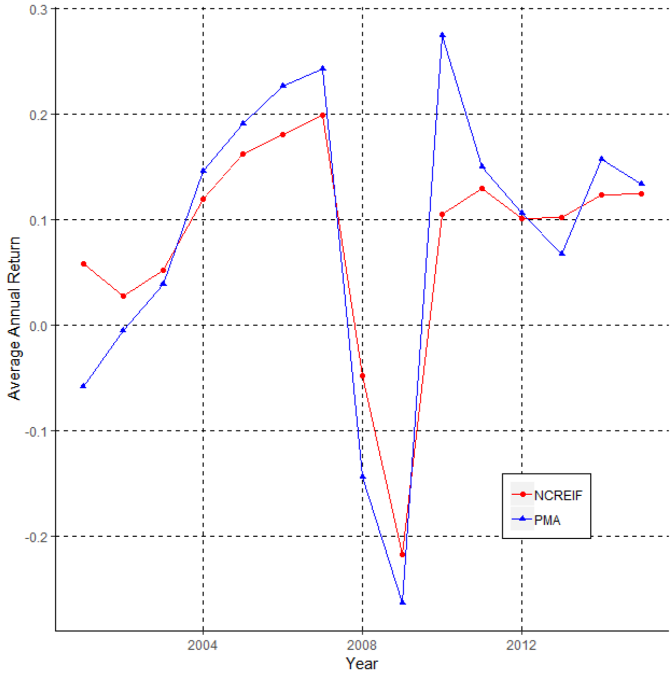
This table shows the regression result of the difference-in-difference model for a placebo test. Model I regresses property market returns on the dummy variable for the placebo shock, D_{Crisis}, the financial center office market dummy, D_{FC_Office}, and their interaction term when using retail markets as the within-city counterfactual. Model II regresses office market returns on the dummy variables for the financial crisis period, D_{Crisis}, the financial center office dummy, D_{FC_Center}, and their interaction term, when using non-financial center office markets as counterfactual. For the placebo shock, we use a sample from 2000 to 2005 with dummy variable D_{Crisis} equal to one for 2004 and 2005 as placebo shock. 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.

	Placebo Shock 2004-2005	
	Model I Office vs Retail	**Model II FC vs NFC**
constant	0.068	0.034
	(0.136)	(0.049)
$D_{Crisis} \times D_{FC\_Office}$	-0.025	0.010
	(0.036)	(0.029)
D_{Crisis}	0.095***	0.063***
	(0.032)	(0.022)
D_{FC_Office}	-0.071***	0.001
	(0.018)	(0.021)
Stock Returns	0.116***	0.119***
	(0.035)	(0.034)
log(SRISK)	0.000	-0.002
	(0.011)	(0.005)
ΔGDP Capita	0.269*	0.447***
	(0.149)	(0.139)
Term Spread	0.341	-0.436
	(0.598)	(0.646)
ΔFloor Space	-0.033	-0.289*
	(0.158)	(0.171)
ΔREIT	-0.041	0.045
	(0.216)	(0.225)
ΔPopulation	0.531*	0.173
	(0.321)	(0.182)
ΔResidential	0.192	0.323**
	(0.165)	(0.153)
ΔClaims	0.020	-0.008
	(0.078)	(0.080)
ΔSentiment	-0.003	-0.005**
	(0.002)	(0.002)
ΔExchange Rate	0.386	-0.011
	(0.316)	(0.326)
Observations	258	243
Adj.-R^2	0.439	0.419

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)

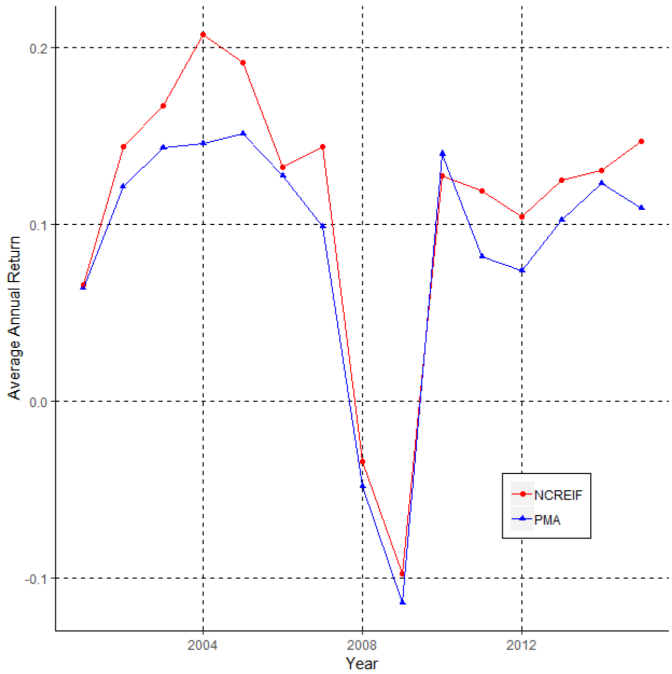
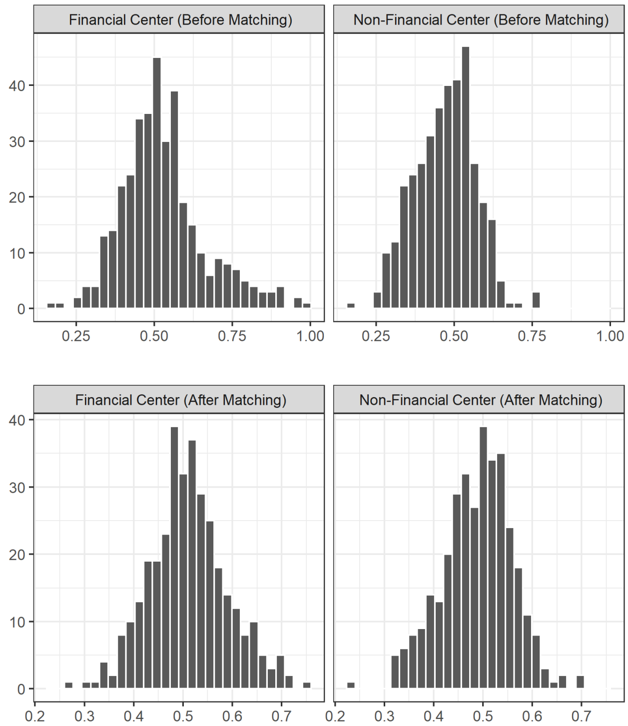


Figure A.2: Matching between Financial (Treated) and Non-Financial Centers (Control)

This figure illustrates the covariate balance between financial (treated) and non-financial centers (control goup). Panel A compares the histograms of the estimated propensity scores for both subsamples before and after matching. Panel B compares the average values of each control variable plotted against the propensity score for both subsamples. The estimated propensity score is based on a probit regression.

Panel A: Histogram of Estimated Propensity Scores (FC vs Non-FC)



Panel B: Common Support by Control Variables (FC vs Non-FC)