Impact of Institutional Investors on Real Estate Risk

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COMMENTS WELCOME.

ABSTRACT

Large institutional investors own an increasing share of the real estate asset market in the U.S. In this paper we seek to understand what are the implications of this recent development. Employing a generalized Hamiltonian Monte Carlo Bayesian procedure we find novel empirical evidence that market entry by large institutional investors predicts higher uncertainty and greater noise in real estate prices in the short and medium run, and lower longitudinal risk in the long run. Our findings point to a significant effect of institutional capital, which serves as a catalyst for structural changes in real estate market volatility.

Keywords: Stochastic Volatility, Institutional Ownership, Investor Size, Real Estate Asset Volatility, Bayesian Estimation, Repeat Sales Model.

JEL classification: C11, C33, C81, G11, G14, R30.

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I. Introduction

Since early 2000s private real estate markets have witnessed the rise of large institutional players. The average real estate portfolio of institutional investors more than doubled between 2000 and 2018 (Cvijanović, Milcheva, and Van de Minne, 2020). As of 2018, the top 10 largest investors had a combined AUM of more than $400B, which constitutes approximately 10% of all investable real estate in the U.S.[1] In this paper, we seek to understand potential implications of large institutional investors trading decisions on the volatility of real estate asset prices.

Ever since Shiller (1981), a large body of literature have sought to understand the origins of volatility in asset (equity) prices. Gabaix, Gopikrishnan, Plerou, and Stanley (2006) show that institutional investors are important for the low-frequency movements of equity prices, and show that their trades can explain excess volatility. Gabaix (2011) goes on to show that idiosyncratic firm-level shocks can explain an important part of aggregate movements and provide a microfoundation for aggregate shocks. Taking this notion to the data, Ben-David, F., Moussawi, and Sedunov (2020) show that institutional ownership induced increases in stock price volatility stem from their granular nature: behavior within the subunits of a large firm displays some correlation that limits internal diversification and exacerbates market impact.

Motivated by this theory, we use a rich micro-level data set on a universe of commercial real estate transactions to study the effects associated with the entry of a large institutional investor in a new market and their effect on (commercial) real estate price risk – both idiosyncratic and longitudinal risk. In particular we look at the largest real estate owner - Blackstone and its entry in a market which previously has not been considered institutional. Such markets are less mature and an entry of a large investor may lead to increases in the idiosyncratic volatility or noise in prices in the short run.

[1] According to Real Capital Analytics, the total amount of "investable" U.S. real estate is $5T. Investable real estate is defined as properties that where sold in its entire history for at least $2.5M. Costar data shows that the total amount of commercial real estate is worth approximately $17T, but this includes mom-and-pop stores, etc.

In the long run, the metropolitan area (MSA) can experience lower overall price volatility through decreases in the longitudinal risk associated with maturing of the market.

Employing a generalized Hamiltonian Monte Carlo Bayesian procedure we find that: 1) Market entry of large (most active) institutional investors predicts higher real estate price uncertainty. 2) This effect is most visible in the short and medium run as a result of an increase in idiosyncratic real estate risk (noise). 3) In the long run, the increase in real estate noise dissipates, and we observe a substantial reduction in the market longitudinal risk (predictability of real estate prices over time). These results suggest that large institutional investors serve as a catalyst for both temporary and permanent structural changes in real estate market stability.

Given the low-frequency trading nature of real estate, its heterogenous nature, and high levels of market segmentation (Cvijanović et al., 2020), measuring uncertainty in real estate prices is fraught with difficulty. Existing literature has primarily relied on proxies of risk, such as the implied or realized volatility of stock market returns, the cross-sectional dispersion of firm profits, stock returns, or productivity, the cross-sectional dispersion of subjective (survey-based) forecasts, or the appearance of certain "uncertainty-related" key words in news publications. In this paper, we use the notion from Jurado, Ludvigson, and Ng (2015), to estimate measures of risk that are as free as possible both from the structure of specific theoretical models, and from dependencies on any single (or small number) of observable economic indicators. The backbone of this approach is to start from the premise that what matters for economic decision making is not whether particular economic indicators, such as real estate prices, have become more or less variable or disperse *per se*, but rather whether the real estate prices have become more or less *predictable*; that is, less or more uncertain.

In order to identify the effect of institutional investor ownership on real estate price uncertainty, we employ an event study set up, similar in spirit to a staggered differences-in-differences approach.

First, using a repeated sales framework, we follow Jurado et al. (2015) and others, in defining risk as the conditional variance of a disturbance that is unforecastable from the perspective of economic agents. Assuming autoregressive innovations, the volatility of the time-varying real estate values could be used to measure *longitudinal* risk, or the predictability in real estate prices over time. However, the volatility defined in this way does not take into account the uncertainty *within* real estate value *itself* (Francke and Van de Minne, 2017). Thus, in order to estimate the overall real estate uncertainty, we explicitly model longitudinal risk (predictability in real estate prices over time) as a time-varying *signal*, and idiosyncratic individual property risk as *noise* in separate transition equations. Similar in spirit to Sagi (2020), idiosyncratic risk, or noise in our model, captures the dispersion in transacting below or above the average transaction price (in our case within an MSA).

Second, we extend this set up to estimate the impact of institutional investors on real estate risk by exploiting variation in institutional ownership induced by the staggered entry of institutional investors in to a market. This is akin to a differences-in-differences (DiD) framework where we compare changes in real estate risk in years before and after the entry of large institutional investors (*the treatment*) in 'treated' markets versus 'control' markets. We estimate this system of equations using the No-U-Turn-Sampler (NUTS) algorithm (Hoffman and Gelman, 2014), a generalized Hamiltonian Monte Carlo Bayesian procedure.

A key assumption that needs to be satisfied in the DiD models is the absence of differential pre-trends for treated and control units. We explicitly address this concern by allowing for time-varying signal and noise in both the measurement and state market equations. Recent literature on staggered DiD design (Sun and Abraham, 2020) highlights that lead or lag coefficients from two-way fixed effect estimations may pick up spurious terms of treatment effects from other periods in settings with variation in treatment timing across units. By allowing for time-varying signal and noise in both state and measurement equations, our identification comes from the differences between post- relative to pre- treatment, irrespective of the trend that might have existed in the underlying variables.

Our empirical tests are built on a large sample of commercial real estate transactions in the U.S. between 2000 and 2019, available through Real Capital Analytics (RCA). For each transaction, we obtain the transaction price and date at time of the buy and sell, as well as the ownership structure. We know the exact buyers and sellers behind each transaction and are therefore able to assign a specific investor to each deal. We have about 50,000 individual investors with Blackstone being by far the biggest and most active one.

Results of our analysis suggest a significant increase in idiosyncratic risk following a market entry by the largest (most active) institutional investor, Blackstone. Real estate noise rises by up to 40% in the first 10 years after treatment. The effect thereafter dissipates, suggesting that the effect of the entry of the largest real estate investor in a new market is associated with a temporary increase in idiosyncratic volatility. As such, large institutional investors can be considered as market disruptors, in the short and medium run. However, in the long run, new market entry results in a permanent drop in the conditional volatility or the longitudinal real estate risk. That implies that most active institutional investors, such as Blackstone, have a long-run risk stabilizing effect. While only observed ten years after entry, this effect is substantial – it results in a 50% reduction in conditional volatility. Taken together, this evidence suggests that most active institutional investors, such as Blackstone, serve as a catalyst for both temporary and permanent structural changes in real estate market risk. While in the short run variation in institutional ownership induced by the staggered entry of institutional investors in to a market results in markets being in the state of flux, due to increased information flow; in the long run, we observe markets maturing, as the price uncertainly is resolved following large trading volumes and more institutional investors entering the market.

A potential concern with our analysis is that institutional investors' decision to enter a particular market is not random, thus potentially introducing a selection bias in our estimation. Given the slow moving nature of real estate markets, we assert that entry of a substantially large investor (i.e. Blackstone is as active as the top 6 largest institutional investors combined, see Table I) creates plausibly exogenous variation in institutional ownership at the market level. We further test this assumption by conducting additional tests that explore the first entry of Blackstone relative to first entry of any other of the top 25 institutional investors. Our results remain quantitatively unchanged.

The positive effect of large institutional ownership on real estate price uncertainty can arise due to a price discovery process in less liquid markets (Ghent, 2020; Sagi, 2020), where (large) trades by (large) investors can generate higher price impact. For instance, investors with low prior exposure to a particular market will be less informed, thus their trading activity will exhibit higher dispersion around the mean price.

Taken together, the results of our analysis suggest that trades by large institutional investors have a greater impact on real estate prices than predicted by the fundamentals. They point to potential for real estate market de-stabilization stemming from large institutional investors' trading activity. Real estate market segmentation coupled with noise-inducing institutional trading activity suggests that excessive concentration in the asset management industry may pose a structural change in prices.

A. Related literature

Our work is part of the emerging literature that studies the effects of different types of investors on real estate markets. Agarwal, Sing, and Wang (2018) empirically test information disadvantages of foreign investors and their learning in global commercial real estate markets, and find that foreign investors pay a premium of 3.6%, on average, relative to local investors for comparable properties in local markets. While Sagi (2020) explains the returns on individual commercial real estate (CRE) assets with a search model, Ghent (2020) aims to explain heterogeneity across cities in CRE trade volumes and investor composition. Badarinza, Ramadorai, and Shimizu (2019) uses a search model to quantify how search frictions arising from differences in investor nationality affect cross-border capital flows. Instead of studying the effects of heterogeneity in nationality, geographical location or liquidity preferences, we study the effects of variations in heterogeneity in institutional ownership. Peng (2020) investigates whether the performance of real estate portfolio of institutional investors affects their acquisitions decisions. The author shows that managers who have higher past portfolio returns make significantly more acquisitions, which in turn have significantly lower risk-adjusted returns.

This paper is related to a broader finance literature showing the impact of demand by institutional investors on asset prices. A vast majority of this literature is focused on equity returns: Sias (1996) and Bushee and Noe (2000) find evidence that increases in institutional ownership are accompanied by a rise in stock volatility. Other studies have established that *aggregate* institutional ownership can affect the volatility and correlation of equity returns and liquidity (Greenwood and Thesmar, 2011; Anton and Polk, 2014; Ben-David, Franzoni, and Moussawi, 2012). Our original contribution is to show that a few large institutions can induce this effect, while being agnostic about sources of uncertainty in prices, and as free as possible both from the structure of specific theoretical models, and from dependencies on any single (or small number) of observable economic indicators. Our novel contribution is to identify large institutional investors as a separate and more important contributor to real estate price uncertainty.

II. Theoretical background

Institutional trading is an important channel through which information is incorporated into stock prices. Piotroski and Roulstone (2004) find that institutional trading is positively associated with idiosyncratic volatility. Hartzell and Starks (2003) find that institutional investors contribute to private information collection and trading.

In the spirit of Ferreira and Laux (2007), our analysis looks at the trading activity of arbitrage-oriented institutional investors in *real estate markets*. The idiosyncratic and illiquid nature of real estate assets, creates incentives to collect private information, which is a central determinant of idiosyncratic volatility. When trading activity is generated, it contributes to this idiosyncratic volatility and to other indications of private information flow. In that sense, our rationale follows Grossman and Stiglitz (1980), who predict that improving the cost–benefit trade-off on information collection leads to more informed trading and more informative pricing.

In contrast to equity markets, real estate markets are characterized by high illiquidity, high transaction costs, and low frequency trading. Gabaix et al. (2006) present a model in which volatility is caused by the trades of large institutions. Institutional investors appear to be important for the low-frequency movements of equity prices, as shown by Gompers and Metrick (2001). In our analysis, shocks in trading activity are created by the trades of large investors. Suppose that proprietary analysis induces a large investor to trade and enter a particular real estate market. Since her desired trading volume is then a significant proportion of the said market turnover, her optimal trading activity will remain large enough to induce a significant price change, as the rate of the information arrival in the market increases.

A stream of research establishes that volatility and information flow are closely associated. Ross (1989) shows that volatility is directly related to the rate of information arrival as an "important consequence of arbitrage-free economics." Strategic models and empirical evidence both establish that informed trade induces volatility (e.g., Glosten and Milgrom (1985) and French and Roll (1986)). Thus, in our setting, observed increase in real estate noise (idiosyncratic volatility) upon institutional investor market entry can be interpreted as the private information being incorporated into real estate prices by informed trading.

Recent empirical evidence also supports this informational interpretation of idiosyncratic volatility. High levels of idiosyncratic volatility are associated with more efficient capital allocation (Durnev, Morck, and Yeung, 2004). Stock prices with high levels of idiosyncratic volatility contain more information about future earnings (Durnev, Morck, Yeung, and Zarowin, 2003).

Motivated by this literature, ours is one of the first studies to explore the effects of institutional investor trading activity on real estate market volatility.

III. Methodology

A. Measuring Real Estate Values over Time

The foundation of tracking constant quality prices over time is based on Hedonic Price Models (HPM). Rosen (1974) explicated the formal microeconomic theory underlying HPMs, although the technique has older roots in consumer and marketing empirical analytics practice (Court, 1939). The basic idea is that heterogeneous goods can be described by their attributes (de Haan and Diewert, 2011). In other words, a good is a bundle of characteristics. In the case of real estate properties, the relevant bundle contains attributes of the building structure and location site of the property. For example, attributes might include the size, age, and type of building, and the distance of the site from downtown or the airport or the nearest subway station. There is no market for the individual characteristics as such, since they cannot be sold separately. In the market for property occupancy, demand and supply in the market for built space (the rental market) determine the characteristics' marginal contributions to the total value of the bundle. The price "index" can subsequently be captured by time of sale dummies. Regression-based techniques are typically used to estimate these marginal value contributions. Such a model is given by;

$$y_{it} = \mu_t + x_i\beta + \epsilon_{it}, \quad \epsilon_t \sim \mathcal{N}(0, \sigma_\epsilon), \quad i = 1, \ldots, P, \tag{1}$$

where i are the individual properties (with P total properties), t is time of sale, x are the covariates (with corresponding coefficient vector β) and ϵ are the residuals. The dependent variable (y) are the log of sales prices. The residuals are assumed to be normally distributed with mean zero and standard error σ.

However, HPMs - in particular commercial real estate properties - are in practice hard to develop. First, properties are heterogeneous in nature, implying many potential value drivers. A second compounding issue is that the number of recorded property characteristics is in most real estate databases quite limited: many value drivers are missing. And when they are sufficiently available, there is the risk of misspecification and overfitting (Francke and van de Minne, 2020). One way to solve this is by using the so-called repeat sales model (RSM), which was first introduced by Bailey, Muth, and Nourse (1963). With the RSM, we replace the covariates with a dummy (δ) per property:

$$y_{it} = \mu_t + \delta_i + \epsilon_{it}, \quad \epsilon_t \sim \mathcal{N}(0, \sigma_\epsilon), \quad i = 1, \ldots, P, . \tag{2}$$

This model is usually "first differenced" - by subtracting the observation at sell from buy - allowing us to drop the property level fixed effect in its entirety:

$$y_{it} - y_{is} = \mu_t - \mu_s + \epsilon_{it} - \epsilon_{is}, \quad \epsilon_{ist} \sim \mathcal{N}(0, 2\sigma_\epsilon), \tag{3}$$

where s is the time of buy, as opposed to t, which is the time of sell. Hyperparameter $\epsilon_{ist} = \epsilon_{it} - \epsilon_{is}$. However, this model has its own caveats. One obvious issue is that we can only estimate this model on properties that sold at least twice, meaning we lose some observations. (Although this issue becomes partly negated as databases mature.) Another issue is that the property might "change" between sales. If it is an obvious change, like change in square footage or property use, the repeat sale is filtered out by our data provider. (See Section IV as well.) However, there are also a lot of possible changes between the sales that we do not observe. These are mostly related to Operating Expenses and Capital Expenditures (OPEX and CAPEX for short). OPEX and CAPEX can be anything from regular maintenance (or the lack thereof) to new HVAC systems for example. As a result, properties with a longer holding period might have a larger variance in sales prices (i.e. higher σ_ϵ). Case and Shiller (1987) solved this by estimating the RSM with weighted least squares, essentially putting less weight on properties with longer holding periods. We solve this by making the noise directly a function of holding period in years. This is given by:

$$y_{it} - y_{is} = \mu_t - \mu_s + \epsilon_{it} - \epsilon_{is}, \quad \epsilon_{ist} \sim \mathcal{N}(0, 2\sigma_\epsilon \times \exp(h_{its}\theta)), \tag{4}$$

where h is the log holding period in years, and θ is the corresponding parameter, which we believe is going to be positive. Note that properties with very low holding periods can also be troublesome, as these might represent "flips" (Clapp and Giaccotto, 1999). Our data provider usually records when a property is bought with the intent to redevelop (which are subsequently filtered out), and they also filter out repeat sales with very low holding periods (less than a year), which corresponds with academic practice (Clapp and Giaccotto, 1999).[2]

B. Measuring Risk

In this paper we are interested in *longitudinal risk* and *idiosyncratic risk*. Longitudinal risk is non-diversifiable and tells us something about the riskiness of the investment. Typically, longitudinal risk is measured by taking the volatility of index returns. However, the volatility defined in this way does not take into account the uncertainty within real estate value itself (Francke and Van de Minne, 2017). Moreover, real estate is different from equity markets, in the sense that it is characterized by a double-sided search market, with relatively little information. As a result, there is a certain level of predictability in real estate prices. We therefore follow the general framework of Jurado et al. (2015), in that we are only interested in the variance around the unpredictable parts of real estate prices. Previous literature (Nagaraja, Brown, and Zhao, 2011; Van de Minne, Francke, Geltner, and White, 2019; Sagi, 2020) found that real estate price returns can best be described by an autoregressive model. As such, we introduce a state equation to the Eq. (4), that implicitly allows for an autoregressive evolution in the innovations. This is given by:

$$\Delta\mu_t \sim \mathcal{N}(\rho\Delta\mu_{t-1}, \sigma_\mu), \tag{5}$$

[2] More recently, Sagi (2020) finds that properties with short holding periods also sell for more while controlling for CAPEX. His reasoning is that such transaction almost never happen, but if they do occur this must happen with a large premium to offset the hefty transaction costs (which can easily be 10% of the initial price) paid for by the owner of the real estate property. Usually, long holding periods are a way to spread out such transaction costs over multiple years.

where ρ is the autogressive parameter, which is fixed to be between $-1 \geq \rho \geq 1$. The standard deviation of the innovations σ_μ will be estimated from the data and is therefore used as *the* proxy for longitudinal risk. Please note that we do not include total returns in our model, but only the asset risk. Geltner and Mei (1995) showed that almost all risk is indeed in the asset market, and not in the income of real estate, which is relatively constant over time (in real terms). However, future research could include the cash flow risk as well.

Idiosyncratic is risk is diversifiable, as the residuals are assumed to be uncorrelated.[3] Idiosyncratic risk is a specific concern for real estate given the low amount of information available in said market. As a result, reservation prices and valuations for similar properties can be quite different from one investor to the other. The idiosyncratic risk is measured by the noise, or parameter σ_ϵ throughout the previous equations.

C. *The effect of investors on risk*

To measure the effect of institutional investors on real estate risk $(\sigma_\epsilon, \sigma_\mu)$, we employ an event study setup. In particular, the event we explore is the first occurrence (entry) of a large investor in market m. Given that not every market had a large investor enter at the same time, we can exploit this heterogeneity in the time of entry to identify the effect large investors have on risk measures discussed above. Further, we seek to understand whether the entry of large investors has a permanent impact on either signal or noise, and its evolution from short to long run.. The measurement equation of such a model is given by:

$$\begin{aligned} y_{mit} - y_{mis} &= \mu_t - \mu_s + \epsilon_{mit} - \epsilon_{mis}, \\ \epsilon_{mits} &\sim \mathcal{N}(0, \big(\sigma_{\epsilon,m} \times \exp(\beta_{1,ds}) + \sigma_{\epsilon,m} \times \exp(\beta_{1,dt})\big) \\ &\quad \times \exp(h_{mits}\theta), \end{aligned} \tag{6}$$

[3]Although in reality most real estate investors are too small to be able diversify effectively.

where subscript d for parameter β_1 is an indicator variable that denotes how many years ago the large investor entered the market (i.e. the market got *treated*). Let us denote the treatment year q. As such, $d = t + 1 - q$ for $t > q$, and zero otherwise. For example, if market m got treated with a large investor at $q = 2005$, then at time of buy (s) in 2001; $d = 0$, and at time of sell (t) at 2010; $d = 6$. Parameter $\beta_{1,d=0}$ is fixed at zero, meaning that the other estimates in vector β represent the premium / discount compared to the non-treated transactions. For every d we estimate a separate parameter. The change in parameter β over d allows us to track whether any shock caused by the treatment is permanent or not. We suppress subscript d for the rest of the equations for readability. Also note that every market gets its own noise parameter σ_ϵ in this setup. A similar setup is used for the state equations.

$$\Delta\mu_t \sim \mathcal{N}(\rho\Delta\mu_{t-1}, \sigma_{\mu,m} \times \exp(\beta_{2,dt})). \tag{7}$$

In this setup, parameter β_2 represents the estimate of the impact of entry of large investors on the longitudinal risk for every year since treatment d, whereas β_1 represents the estimate of the treatment effect of entry of large investors on noise/idiosyncratic risk. Both $\beta_{1,d}$ and $\beta_{2,d}$ are modeled as random walks:

$$\Delta\beta_{k,d} \sim \mathcal{N}(0, \sigma_{\beta_k}), \tag{8}$$

where $k = \{1, 2\}$. The model as shown in Eqs. (6) – (8) will be referred to as the *Baseline Model* or BSM henceforward.

This (and subsequent) model(s) will be estimated using the No-U-Turn-Sampler introduced by Hoffman and Gelman (2014). We will use largely uninformative priors for all the parameters (Gelman, 2006). The No-U-Turn Sampler has been applied to real estate before, see for example Van de Minne et al. (2019); Rolheiser, van Dijk, and van de Minne (2020).

D. Additions to the Baseline Model

We introduce two additional models to augment the *Baseline model* introduced in Section III.C. The first is denoted *Separate Index Model (SIM)*. With this model we change the state equations to allow for separate indexes per market m. Even though real estate markets tend to co-move to a certain extent, due to the effects well-integrated of capital markets affecting investors cap rates, *space markets* impact prices equally (Van de Minne et al., 2019). Space markets are segmented based on the location, as rents are negotiated locally. For example, an office in New York does not competed with an office in Los Angeles. The new state equation now becomes:

$$\Delta\mu_{mt} \sim \mathcal{N}(\rho_m \Delta\mu_{m,t-1}, \sigma_{\mu,m} \times \exp(\beta_{2,dt})). \tag{9}$$

In essence, our empirical strategy can be thought of as a Differences-in-Differences approach. We estimate the impact of institutional investors on real estate risk by exploiting variation in institutional ownership induced by the staggered entry of institutional investors entry in to a market. This is a kin to a differences-in-differences framework where we compare changes real estate risk in years before and after the entry of large institutional investors (*the treatment*) in 'treated' markets versus 'control' markets. A key assumption that needs to be satisfied in the Diff-in-Diff models is that of parallel trends for treated and control markets. In our final model - denoted *StochVol Model (SVM)* - we explicitly address this concern by allowing for time-varying signal and noise in both the measurement and state equations per market, while also keeping the separate indexes per market. Recent literature on staggered differences-in-differences design (Sun and Abraham, 2020) highlight that lead or lag coefficients from two-way fixed effect estimations may pick up spurious terms of treatment effects from other periods in settings with variation in treatment timing across units. By allowing for time-varying signal and noise in both state and measurement equations, our identification comes from the differences between post- relative to pre-treatment, irrespective of the trend that might have existed in the underlying variables.

The new measurement equation now becomes:

$$
\begin{aligned}
y_{mit} - y_{mis} = \mu_t - \mu_s + \epsilon_{mit} - \epsilon_{mis}, \qquad (10)\\
\epsilon_{mist} &\sim \mathcal{N}\big(0, \big(\sigma_{\epsilon,ms} \times \exp(\beta_{1,ds}) + \sigma_{\epsilon,mt} \times \exp(\beta_{1,dt})\big)\\
&\quad \times \exp(h_{mits}\theta).\\
\Delta\sigma_{\epsilon,mt} &\sim \mathcal{N}(0, \omega_1). \qquad (11)
\end{aligned}
$$

For the state equation we now get:

$$\Delta\mu_{mt} \sim \mathcal{N}(\rho_m \Delta\mu_{m,t-1}, \sigma_{\mu,mt} \times \exp(\beta_{2,dt})). \qquad (12)$$

$$\Delta\sigma_{\mu,mt} \sim \mathcal{N}(0, \omega_2). \qquad (13)$$

Note that we use a random walk for the innovations of the signal and noise, which is a specific form for Stochastic Volatility Models (Bos and Shephard, 2006). Identification of β for the SVM comes from two sources. First, the time varying signal and noise are estimated as a structural time series, with variance ω^2. Any "jump" caused by the treatment that is sufficiently large (i.e. larger then "normal" ω) will therefore be captured by β. Second, *within one year*, the years since treatment (d) will be different for the different markets.

IV. Data and Descriptive Statistics

Our analysis uses transaction data from Real Capital Analytics (RCA). RCA captures approximately 95% of all commercial property transactions in the United States over $2.5 million.[4] They have a dedicated research team of over 200 that finds - and enters into their database - real estate deals, even in non-disclosure states. Their data runs from 2000 until 2019 and contains over half a million individual transactions. We look in particular at transactions that are repeat sales. Before we proceed with the repeat sales transactions, we first calculate who the largest investors are, measured

[4] However, once a property is in their database they will keep tracking it, even if subsequent sales are below that threshold.

by how active they are in the real estate market. Similar to Cvijanović et al. (2020), it is noteworthy that RCA knows whenever a company buys on behalf of another company. As a result, we can accurately track who is investing in what market. Table I gives the 10 most active investors, ranked by the amount of transactions, including buying and selling, they took part in between 2000 and 2019.

[Place Table I about here]

Unsurprisingly, Blackstone has been responsible for most transactions. Blackstone is also by far the largest investor in the US and internationally in terms of the value of their real estate portfolio according to Cvijanović et al. (2020). Note that Blackstone itself was responsible for as many transactions as the numbers 2 through 6 *combined*. In fact, given that we observe a total of a million transactions (both buy and sell), Blackstone was involved in 1.5% of all transactions. This number can be considered high, given that we identify $47,622$ individual investors in our data. Our main treatment is therefore the moment Blackstone entered a market. Given Blackstone's size which is much larger the the rest of the investors in both number of transactions and asset size, we are confident that the treatment is exogenous and are not concerned with endogeneity associated with Blackstone's entry. We discuss this in more detail in the results section where we also provide robustness specifications.

To construct our repeat sales, we use the algorithm and filters provided to us by RCA. Only if the property did not change between sales (because a redevelopment or a major addition to a building), are multiple transactions of the same property considered to be repeat sales. Repeat sales with a holding period of a year or less are also excluded, as these can represent "flips". Next, we omit any markets that were already treated (i.e. Blackstone has entered the market) before our data starts, which is in 2000. Given that these observations are left censored, and the fact that these markets will not give identification to our variable of interest (β), we omit them from further analysis. This also makes the estimation more tractable. The descriptive statistics on the sales prices and the year of sale of sale are given in Table

II. Data on the markets included in our sample, and when they got treated is given in Table III.

[Place Table II about here]

[Place Table III about here]

The average buy price is $13.7mn with a standard deviation of $20mn (Table II). Some of the smallest transactions are of a value of around $3mn and some of the largest ones of $30mn. On average, prices where higher during the sale, compared to buy. This is also reflected in the (log) returns between sales, which is 0.156 on average. Note that the (log) return is our dependent variable in the regression models. The standard deviation of the (log) returns is quite high with 0.409, meaning there is a lot of heterogeneity in returns. The average year-over-year (log) return is 4.4%. The average holding period is slightly over 6 years with a standard deviation of 3.5 years. Some of the longest holdings periods, 90th quantile, take 11 years.

In total we observe over 12,556 repeat sales, or approximately 25 thousand transactions. We find a considerable drop in transactions during the Global Financial Crisis (GFC) of 2008, which was expected. Repeat sale transactions go from about 1,900 in 2007 to 503 in 2009. In 2015 transaction volume is at an all-time-high with 1,925.

Most cities in our data set can be considered second-tier cities for commercial real estate investment. Blackstone was already invested in markets like Manhattan, LA county, Boston, Chicago, etc. However, some markets are in a larger metropolitan area, like the New York Boroughs, Long Island, Inland Empire, Ventura county and Miami. Overall, there is a good mix - geographically - of markets included in our sample. Interestingly, many of the markets in our sample got first treated (q) by Blackstone in 2004. Still, there is a good mix available treatment years to estimate the effect of treatment as well with the earliest entry being in 2003 and the latest in 2010. By 2010, Blackstone has invested in every MSA in the RCA data.

The entry in 2004 is in line with the beginnings of the housing boom prior to the GFC and the expansion of Blackstone in the real estate market, although Blackstone's real estate business was founded in 1991. Prior to that Blackstone was active as a private equity management firm in leveraged buyouts. Blackstone acquired Prime Hospitality, which is one of the nation's premiere lodging companies, owns, manages, develops and franchises more than 250 hotels throughout North America, and Extended Stay America in 2004. Blackstone followed these investments with the acquisition of La Quinta Inns Suites in 2005. Back in 2004, Blackstone's Real Estate Group had raised five funds, representing over $6 billion in total equity, and had at a time already a long track record of investing in hotels and other commercial properties. In 2007 Blackstone went public and become the largest US IPO since 2002. Since going public, Blackstone has multiplied eight-fold the equity capital it devotes to real estate, to $163 billion.

V. Results

A. Main Results

Figure 1 gives the estimates of β, our main focus. The results for the Baseline Model (BSM) are given in Figures 1a – 1b. Here we find a negative, but not-significant, effect of our treatment on the longitudinal risk (signal). We do find a positive (and mostly significant) effect on noise in the first 10 years. The largest effect has an average posterior mean of 0.2, which means a temporary 22% increase in noise, when Blackstone enters in a new market for the first time. This means if an MSA has not had Blackstone as a real estate investor, once Blackstone buys a property in that MSA, the idiosyncratic volatility of the house prices in that area will gradually go up and increase by up to 22% after 7-8 years. Thereafter the trend reverses gradually. After 10 years, this effect becomes negative and significant. The volatility drops by somewhat less than 20% 15 years after investor's first entry to then gradually revert to zero after 20 years. The effect of the entry of the largest real estate investor in a new market on idiosyncratic house price risk can be seen as a transitory shock, however, one that takes 20 years to reverse all else equal.

Figures 1c – 1d provide the results for the SIM specification. The results correspond to earlier findings, but the significance levels are different. Here we also find that our treatment has a negative effect on the longitudinal risk (signal), but now it is largely significant at the 5% level. We find that the idiosyncratic risk reduces by 50%, 15 years after treatment. The negative effect on the idiosyncratic risk (noise) 13 years after treatment is mostly gone now. The positive effect on noise is also somewhat larger.

The "full" StochVol model (SVM) is given in Figures 1e – 1f. This is our preferred model which will use later on to estimate further specifications to check the robustness. The reason is as mentioned in the Methodology Section, that the SVM model accounts for time varying signal and noise unlike the BSP model which makes the estimation more precise. This can explain why the results change from the BSM model. The results are very similar in posterior mean as in significance to the findings of the SIM specification.

Similar to the two models above, we see a significant increase in idiosyncratic risk following a market entry by Blackstone. Noise rises by up to 40% in the first 10 years after treatment. The effect thereafter becomes insignificant suggesting that the effect of the entry of the largest real estate investor in a new market is associated with a temporary increase in idiosyncratic volatility. It takes ten years as this is an effect following a single real estate transaction and because real estate is a slow moving asset and it takes considerable amount of time for effects to feed into the rest of the market and to affect pricing and therefore risk. The effect can be interpreted as one that causes disruption on the market increasing noise in prices as a result of the entry. However, in Figure 1e it becomes clear that there is also a long term effect of Blackstone's entry - a permanent drop in the conditional volatility or the signal as we call it. That means that Blackstone has a long-term risk-reducing effect which can be seen as the market maturing. The significant effect is only observed after the tenth year, but it is substantial. Our treatment results in a 50% lower signal. Therefore Blackstone seems to serve as a catalyst for temporary and permanent structural changes to price risk which might be associated with an initial effect of price search and uncertainty and a follow-on effect of market maturing perhaps due to in increase in trading volumes and more institutional investor entering the market.

[Place Figure 1 about here]

B. Other Estimates of Our Main Models

Next we discuss some of the other estimates from our model. Table IV gives a summary of the some of the (hyper)parameters. First of all, we find that properties with longer holding periods (in log years) have higher levels of noise. This is in line with previous literature (Case and Shiller, 1987), and was thus expected. Whenever the holding period doubles, noise increases with more than 30%. The predictability of commercial real estate prices is obvious when looking at the estimate of the autoregressive ρ parameter of the index returns ($\Delta\mu_t$). For the BSM we get an estimate of 0.81. The average estimate for all the markets for the SIM (SVM) is 0.37 (0.44). This is in line with our preferred choice of a model being SVM which is associated with less autocorrelation. The average noise levels (σ_ϵ) seem quite low (0.1 for both BSM and SIM), but note that this is the noise for when holding periods are zero. If we take an average holding period of 10 years for example, we would have to multiply the noise term with 1.7 in order to get an average market noise. The unpredictability of the index returns (σ_ρ is large) is considerably larger for the BSM, as compared to the other models. This is not surprising. Given that prices are partly space market driven, having a separate index per market helps explain price movements better. The estimates ω are difficult to interpret easily. However, the estimate ω_1 is considerably higher than ω_2 (with 0.13 versus 0.04 respectively). One way to interpret this, is that noise varies more over time than signal does.

[Place Table IV about here]

Figure 2 gives a few examples of the estimated time-varying parameters. Figure 2a gives the estimates of our signal parameter μ_t for the BSM, which can be interpreted as an (log) index. Prices first go up, then crash during the

GFC, and recovering again after 2010. For the SIM and SVM parameters over time we look at a few markets as examples instead of all the time series for every market in order to conserve space. We picked the first four markets as an example: Baltimore, Birmingham (AL), Boulder, and Brevard County. The estimates of μ_t are very similar between the SIM and SVM (Figures 2b – 2c), and are in line with the general pattern from the BSM in Figure 2a. The only exception here is Boulder where prices did have a peak before the GFC. As expected, the noise varied more over time (Figure 2d) compared to the signal (Figure 2e). Although there is a lot of variation *between* the markets for signal, Brevard County has a longitudinal risk (signal) of 0.048, whereas Boulder "only" has a longitudinal risk of 0.015. The fairly constant line for signal for each of the markets is under the assumption of no market entry by a large investor. If Blackstone enters the market, the line will shift downwards, as we demonstrated in the previous section. The similarity in the longitudinal risk pattern over time across the markets is in line with the parallel trend assumption of classic difference-in-differences (DiD) models. While the risk is differently high, in the absence of entry shocks, there is no major difference in the risk over time. The idiosyncratic risk instead varies more over time – it is falling in Boulder and Baltimore from 2000 to 2014 while it is increasing in Brevard County throughout our sample period, 2000-2019.

[Place Figure 2 about here]

C. Robustness

As discussed above, the entry of Blackstone is associated with significant changes to price risk. To be able to cleanly identify whether the effect is due to Blackstone alone or to the presence of large investors in general, we conduct some robustness specifications. With our first robustness check (R1), we omit all markets from our data, that already had a top 25 investor in the market, before Blackstone entered it. This means that Blackstone entered before any of the other 25 largest investors. In these markets the treatment is more "unexpected" and can be assumed to be exogenous to the market choice of Blackstone. This means, Blackstone would enter in a market first and the choice of this market would be exogenous to what happens in that market. One reason for the Blackstone entry into a market with no large institutional investors might be predicated on Blackstone's size and the need to diversify its real estate portfolio.

When focusing on markets where Blackstone was the first large institutional investor, we lose a lot of observations. More specifically, we end up with only 2,159. All the larger markets in our data are now not included anymore in the sample, like the NYC boroughs.[5] For our second robustness specification (R2), we do it the other way around. We define the treatment as a top 25 investor entering the market, before Blackstone did so. We have 1,932 observations for this specification. The results for the SVM model are reported in Figure 3.

[Place Figure 3 about here]

Our first Robustness model (Figures 3a – 3b) shows that the results remain similar to our earlier findings in the main model, although slightly less significant. This is not per se surprising given how many observations we lose. With our second Robustness model, we find no significant results at all. This confirms our findings above that the effect is driven by Blackstone alone and not by large investors per se. First, Blackstone moving first into a less mature market raises the noise in the pricing of real estate in that market. More investors can follow suit and enter said market and cause further noise until after about 8-9 years when the idiosyncratic risk becomes insignificant. Thereafter, we see that Blackstone's entry significantly reduces the longitudinal risk in that market – other large investors do not have the same effect. This seems to be a Blackstone effect – with Blackstone entering the market, large investors can follow and this can lead to lowering overall price uncertainty and maturing of the market.

[5] More specifically, the markets in this sample are: Co Springs, Fresno, Greensboro, Hartford, Minneapolis, Naples, Oklahoma City, Reno, and Santa Rosa.

VI. Concluding Remarks

Using a rich micro-level data set on a universe of commercial real estate transactions in this paper we study the effects of institutional ownership on (commercial) real estate price uncertainty. Employing a generalized Hamiltonian Monte Carlo Bayesian procedure we find that: 1) Market entry of large (most active) institutional investors predicts higher real estate price uncertainty. 2) This effect is most visible in the short and medium run increase in idiosyncratic real estate risk (noise). 3) In the long run, the increase in real estate noise dissipates, and we observe a substantial reduction in the market longitudinal risk (predictability of real estate prices over time). These results suggest that institutional investors serve as a catalyst for both temporary and permanent structural change in real estate market stability.

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Tables

Table I. Top 10 Most Active Investors. Data is provided by Real Capital Analytics (RCA) Inc. Note that Blackstone acquired Gramercy Property Trust in 2018.

Rank	Company	Transactions
1	Blackstone	14,615
2	Gramercy Property Trust	3,717
3	Prologis	3,505
4	Goldman Sachs	3,079
5	GE Capital	2,824
6	Starwood Capital	2,759
7	Colony Capital (REIT)	2,758
8	Inland RE Group	2,680
9	Brookfield AM	2,661
10	PGIM Real Estate	2,578

Table II. Descriptive Statistics. Data is provided by Real Capital Analytics (RCA) Inc. *st.dev* = standard deviation. *q10* is the 10^{th} quantile, and *q90* is the 90^{th} quantile. YoY is year on year.

	mean	**st.dev**	**q10**	**q90**
price (buy)	\$ 13,705,081	\$ 20,122,599	\$ 3,000,000	\$ 30,560,000
price (sell)	\$ 16,655,696	\$ 24,301,597	\$ 3,241,250	\$ 37,975,000
(log) return	0.156	0.409	-0.389	0.634
(log) return (YoY)	0.044	0.095	-0.056	0.164
holding period (years)	6.230	3.487	2.000	11.000
Transactions by year of sale / buy				
2000	407			
2001	491			
2002	631			
2003	766			
2004	1,096			
2005	1,837			
2006	1,898			
2007	1,911			
2008	1,051			
2009	503			
2010	784			
2011	1,093			
2012	1,486			
2013	1,637			
2014	1,874			
2015	1,925			
2016	1,628			
2017	1,455			
2018	1,317			
2019	1,322			
Total observations		12,556		

Table III. Counts and Treatment Year for All Markets. Data is provided by Real Capital Analytics (RCA) Inc. N is number of observations, q is the treatment year (i.e. when Blackstone entered the market).

Market	N	q	Market	N	q
Baltimore	462	2003	Naples	90	2004
Birmingham (AL)	156	2004	New Haven	92	2010
Boulder	115	2006	No NJ	833	2004
Brevard Co	80	2006	Norfolk	151	2004
Camden, NJ	157	2004	North Bay	96	2007
Charleston	150	2006	NYC Boroughs	1,174	2004
Cincinnati	254	2003	Oklahoma City	205	2004
Co Springs	209	2004	Omaha	91	2007
Columbia	133	2007	Orlando	739	2004
Columbus	272	2004	Pittsburgh	91	2004
Florida Panhandle	95	2006	Providence	145	2010
Fort Myers	154	2006	Reno	160	2004
Fresno	117	2004	Richmond	155	2004
Greensboro	139	2004	San Antonio	161	2002
Greenville	184	2004	Santa Barbara	94	2007
Hartford	125	2003	Santa Rosa, CA	116	2004
Honolulu	77	2005	Sarasota	166	2004
Indianapolis	163	2006	Tallahassee	93	2004
Inland Empire	983	2006	Tampa	992	2004
Long Island	297	2010	Tucson	255	2004
Louisville	111	2006	Tulsa	130	2004
Miami/Dade Co	818	2004	Vallejo-Fairfield, CA	88	2004
Minneapolis	614	2003	Ventura Co	192	2007
Modesto	113	2007	Westchester	161	2004
			Worcester	108	2005

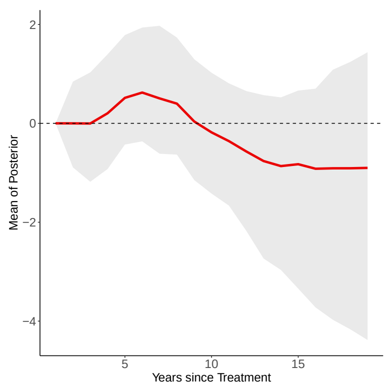
Table IV. Estimates of the (Hyper)Parameters. Average of the estimates is given in the Table. Standard deviation of the corresponding variables are given in parenthesis, if applicable. BSM = Baseline model, SIM = Separate Index Model, SVM = StochVol Model.

	BSM	SIM	SVM
θ (holding period)	0.288	0.250	0.262
ρ (AR parameter)	0.810	0.366 (0.230)	0.440 (0.205)
σ_ϵ	0.104 (0.012)	0.101 (0.010)	-
σ_μ	0.782 (0.104)	0.167 (0.051)	-
ω_1 (noise)	-	-	0.129
ω_2 (signal)	-	-	0.041
N		12,556	

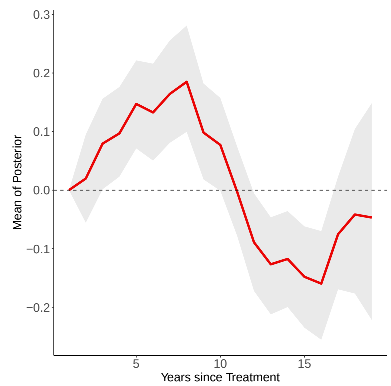
Figures

Figure 1. The Effect of Blackstone on Real Estate Risk. Solid line gives the mean of the posteriors. Bars represent the 95% credible intervals. *BSM* = Baseline model, *SIM* = Seperate Index Model, *SVM* = StochVol Model. Noise tracks parameter β_1, which captures the idiosyncratic risk, and signal tracks parameter β_2, which measures the change in longitudinal risk. The models are estimated using Bayesian techniques.

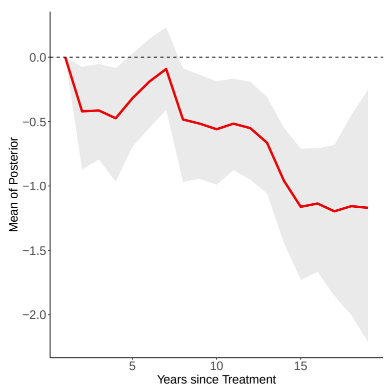
(a) BSM (signal).



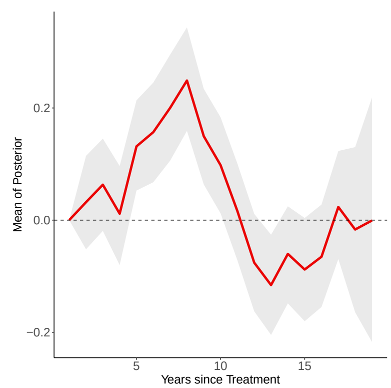
(b) BSM (noise).



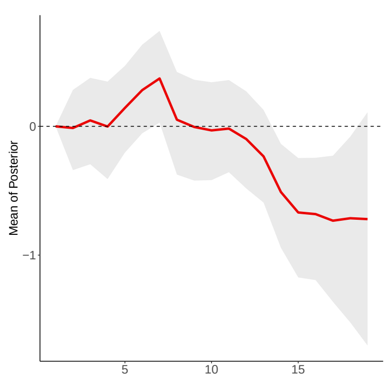
(c) SIM (signal).



(d) SIM (noise).



(e) SVM (signal).



(f) SVM (noise).

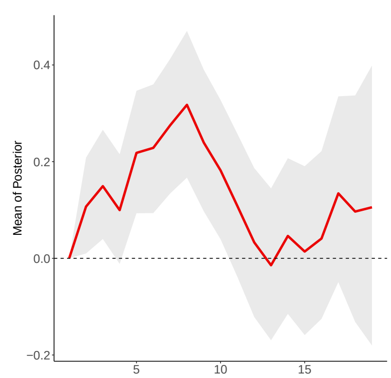
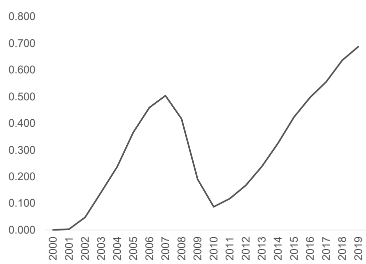
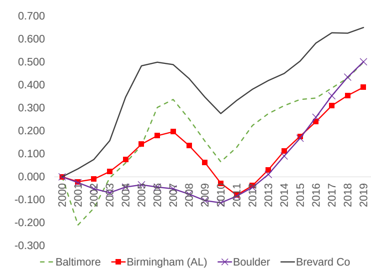


Figure 2. Estimated Indexes. *BSM* = Baseline model, *SIM* = Seperate Index Model, *SVM* = StochVol Model. Parameter μ gives the (log) "price index", $\sigma_{\epsilon_{m,t}}$ gives the evolution of noise (SVM) over time per market, and $\sigma_{\mu_{m,t}}$ is the change in signal over time per market. We only represent the first 4 markets of our sample to conserve space. Others are available upon request.

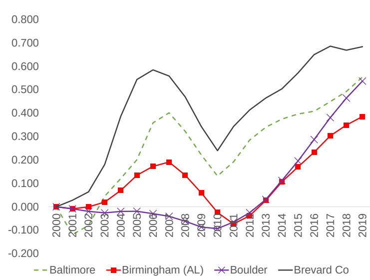
(a) BSM μ_t.



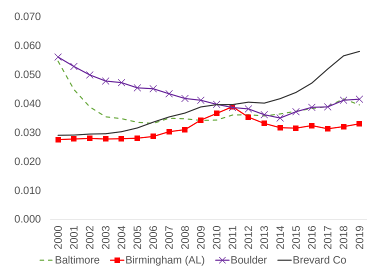
(b) SIM $\mu_{m,t}$.



(c) SVM $\mu_{m,t}$.



(d) SVM $\sigma_{\epsilon_{m,t}}$.



(e) SVM $\sigma_{\mu_{m,t}}$.

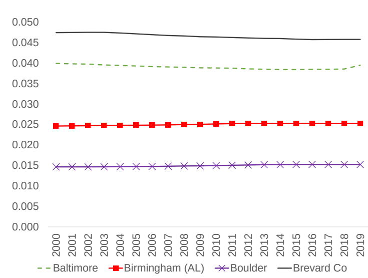
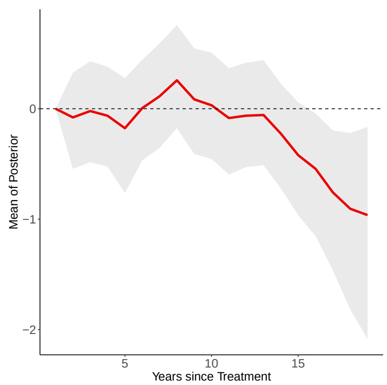
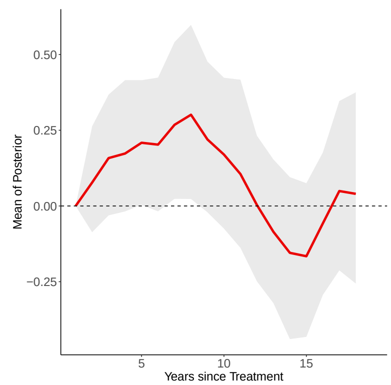


Figure 3. Outcomes of Robustness. *SVM* = StochVol Model. Noise (Signal) tracks parameter β_1 (β_2). With R1 (Robustness model 1), we only enter markets that Blackstone was first to, compared to the top 25 investors. With R2 (Robustness 2), we only use markets that where first visited by any investor in the top 25, excluding Blackstone.

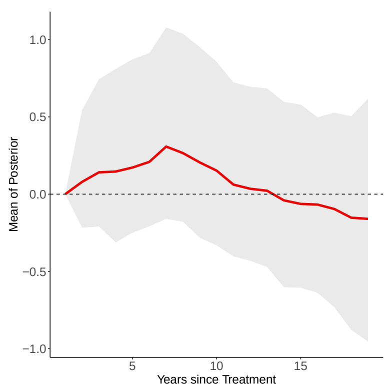
(a) R1 – Blackstone (signal).



(b) R1 – Blackstone (noise).



(c) R2 – 25 top investors (signal).



(d) R2 – 25 top investors (noise).