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An Innovative Approach to Identify Latent Overconfidence and Disposition Effects in Frictional Real Estate Markets

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The operating decisions of investors can be irrational. This research proposes an approach to measure overconfidence bias and the disposition effect based on real estate rental decisions, and disentangle from market friction. Irrational operating decisions transform into impacts on real estate rentable supply responsiveness and market illiquidity. Analyzing US office market data from 2005 to 2019, the empirical findings confirm that the disposition effect significantly impacts supply responsiveness, alongside the effects of overconfidence, regulations and geographical barriers. Friction is the leading cause of market illiquidity, and the level of market illiquidity due to the disposition effect is higher than the overconfidence bias; thus, the disposition effect more frequently occurs.

Keywords

Overconfidence, Disposition Effect, Friction, Supply Responsiveness, Market Illiquidity, Commercial Real Estate

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1. Introduction

Stock markets are typically mark-to-market; therefore, the irrational behavior of equity investors is discernible in such frictionless markets. However, friction is substantial in real estate markets, which are driven by decentralized trading, a limited number of buyers and sellers, and high transaction costs. This means that when rational investors decide to sell or buy, they must wait to execute their decisions. Thus, friction misrepresents the behavior of investors, and makes it difficult to accurately distinguish between rational and irrational behaviors in real estate markets.

The existing literature measures overconfidence, which leads to housing price bubbles, by conducting surveys (Shiller, 2015). The studies examine the loss aversion of homeowners and commercial real estate (CRE) investors in bust periods by calculating the difference between the previous and expected selling prices, and truncating from below at zero (Genesove and Mayer, 2001; Bokhari and Geltner, 2011). Furthermore, the overconfidence of chief executive officers (CEOs; including over-optimism of chief financial officers) in real estate investment trusts (REITs) is examined by measuring the purchase and sales of the own-company stock of each CEO (Eichholtz and Yönder, 2015; 2022). Practitioners also implicitly show that there are a handful of behavioral biases of CRE investors, including framing, anchoring and home biases, and loss aversion by observing market feedback (Richardson et al., 2017).[1] Lizieri (2025) explains the deviation in CRE by using a rational model with private markets, information asymmetry, costly information and heterogeneous assets. Aside from publicly-traded REITs, the friction in direct real estate investment, which can distort the timing of executing investment decisions, should be discussed. Moreover, many studies in the empirical literature suggest ways to identify overconfidence bias, including standard psychological surveys to measure confidence, with controls for knowledge (Ortoleva and Snowberg, 2015); estimates of residuals from a regression of self-confidence test scores with controls for competence (Grinblatt and Keloharju, 2009); and ranking the population to estimate mean beliefs (Benoit and Dubra, 2011). Since

[1] Due to framing bias, the long-term performance of prime property is more volatile than the national average. Anchoring bias means that participants anchor to a range of measures with low predictive values. In particular, investors fixate on capital gains rather than income returns; this leads to additional risk exposure if a market corrects. Loss aversion hinders the sales of an asset at loss. Market correction proceeds in three waves. When the initial fall in property prices occurs, investors are prepared to ride this out and do not immediately sell out. During the second wave of the correction, some continue to hold on, even suffering an additional slide. The third wave of selling pressure eventually causes complete investor capitulation and a steep decline in capital values. Due to complicated procedures, selling commercial real estate requires a longer period of time. Home bias leads to over-investing in domestic assets, and hence exposes portfolios to concentration risk.

overconfidence bias is relatively latent, it is not easily self-perceived. Supported by the findings on the irrationality of professional or institutional investors in stock markets and corporate finance (Gervais et al., 2011; Baker and Wurgler, 2013; Bodnaruk and Simonov, 2016) and the overconfidence of CEOs in REITs (Eichholtz and Yönder, 2015), I argue that relatively sophisticated investors may also be overconfident. Thus, the previous assumption in the literature that overconfident investors tend to be ignorant might not be supported. My argument is supported by a systematic literature review (Singh et al., 2023), where institutional and professional investors are affected by behavioral biases.

The disposition effect is easier to estimate in stock markets, which is done by tracking individual portfolios (Shefrin and Statman, 1985; Chou and Wang, 2011; Li and Yang, 2013; Chang et al., 2016). However, unrealized gains or losses in real estate assets are difficult to measure due to infrequent and non-consistent valuation. Furthermore, the method used in stock markets may not apply to real estate. The disposition effect involves the loss aversion of investors. Bokhari and Geltner (2011) measure loss aversion in CRE pricing and find that more sophisticated investors have more assertive loss aversion behavior in asking prices. Few studies in the literature have investigated overconfidence bias and the disposition effect in indirect real estate investments such as REITs and mutual funds (Ro and Gallimore, 2014; Eichholtz and Yönder, 2015; 2022). These findings support the phenomenon of irrationality in real estate capital markets, and I believe that investors also exhibit irrational behavior in their operating decisions.

Therefore, this study proposes an innovative approach to identify overconfidence bias and disposition effects, as well as market friction, based on the operating decisions of real estate investors. The work quantifies their extent at the US metropolitan statistical area (MSA) level by using a novel dataset, and investigates how two kinds of irrational biases affect real estate supply responsiveness and market illiquidity. In general, the study makes four contributions: (1) conceptualizes how the operating decisions of overconfident investors and others with a disposition tendency determine related real estate supply responsiveness and equilibrium vacancy, which is a measure of market illiquidity; (2) proposes a new identification approach, to observe two kinds of investor irrationalities based on more routine operating decisions instead of occasional investment decisions, and also distinguishes from market friction; (3) provides first and foremost evidence of MSA-level overconfidence bias and disposition effects; and (4) discusses and empirically shows how these two kinds of aggregate irrational biases affect real estate supply responsiveness and market illiquidity.

Suppose the existing empirical strategies based on sales transactions, asset portfolios, and psychological tests are applied to measure these biases at the MSA level. In that case, several significant challenges are present: (1) infrequent sales transactions; (2) significant market friction driven by taxes, regulations, and insufficient buyers; (3) less frequent realization of real estate valuation; (4) less transparency of the real estate portfolios of private investors; (5) misestimation of the mean belief for measuring overconfidence; and (6) unreliable responses in psychological tests. All of these can cause the misestimation of overconfidence bias and disposition effects. Therefore, my innovative approach addresses all these challenges.

In short, I identify the failure of investors who forgo secure income inflow by permitting sub-leases, and instead, seek a tenant for direct leasing. Then, I compare their situation with the failure of rational tenants who want to sublet. Therefore, I calculate the ratios of direct-to-sublease availability (or vacancy), to measure overconfidence bias. On the other hand, I propose to observe how CRE investors decide to operate depreciated properties (i.e., reduction in value due to wear and tear), to identify the disposition effect if investors have a tendency toward disposition, even when the prime vs non-prime rental gap is sufficiently large enough to cover renovation costs (RCs). They will still hesitate to upgrade depreciated properties. Therefore, the likelihood of a property upgrade concerning a rental gap larger than the threshold decreases with the extent of the disposition effect.

After measuring two kinds of irrational biases, I examine how these biases affect real estate supply responsiveness and market illiquidity. I adopt Engle-Granger panel error correction models to analyze the novel dataset of 38 MSA-level office markets during 2005Q1-2019Q4 (i.e., which covers 61% of the office workforce in the US). Such elastic office demand estimates indicate that tenants tend to be rational. I conclude that the disposition effect in each MSA significantly impacts supply responsiveness (i.e., rentable supply decreases when rent rises) among overconfidence bias, regulations, and geographical barriers. Overconfidence bias, in most MSAs, leads to inelastic rentable supply. Compared with the disposition effect, the aggregate behavior of overconfident investors deviates less from market norms.

I measure market illiquidity by using equilibrium vacancy; i.e., space not used in equilibrium, like non-trading stocks. To disentangle irrational effects from market friction, I apply the approach in Marcato and Tong (2023) to identify rental market friction with potential frequent turnover due to the net business survival of new firms. The results of the supply-side cointegration equation are used to estimate equilibrium vacancy due to the disposition effect, overconfidence bias, and market friction. Based on my findings, market friction is the leading cause of market illiquidity. In most of the MSAs in the sample, market illiquidity (measured by equilibrium vacancy due to the disposition effect) is higher than overconfidence bias. This finding implies that the disposition effect occurs more frequently. Also, a highly positive correlation between the supply responsiveness of overconfident investors and their derived equilibrium vacancy suggests that their inaccurate market forecasting leads to over-reaction, and their new over-supply of a specific rentable office class is not trading.

Relative to Marcato and Tong (2023) who focus on search friction, this study contributes by quantifying the role of behavioral biases in shaping supply responsiveness and market liquidity. By developing novel MSA-level measures of overconfidence and disposition based on operating decisions, the study provides empirical evidence of latent irrationality in real estate markets. This complements the friction-based literature and highlights the importance of behavioral heterogeneity in explaining illiquidity in CRE.

The paper is organized as follows: the next section presents my conceptual framework. In Section 3, I explain the empirical strategy and describe the data. Section 4 discusses the main results, and Section 5 summarizes the robust test results. Finally, I draw my conclusions.

2. Conceptual Framework

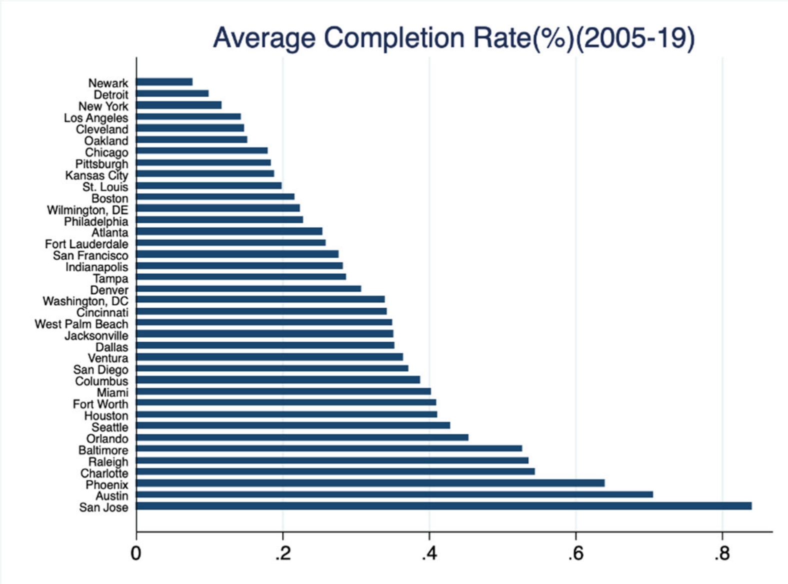
2.1 Why Equilibrium Vacancy and Delays in Supply Responses should be attributed to Biased Investors.

In a labor market, additional job vacancies are generally created with government aid to facilitate search and matching; hence, the process turns out a natural rate of job vacancies. Thus, job vacancies in an equilibrium state could be attributed to governments. However, this is not the case in real estate, because vacant property taxes show us that local governments discourage vacant space.[2] Moreover, rational real estate investors will minimize vacant space in their assets and hence reduce their loss. In other words, rational investors do not cause equilibrium vacancy. For the office sector in 38 MSAs, the existing supply plays a more dominant role, as a new development always remains at the deficient level of 0.1%-0.8% of the total stock (Figure 1). Therefore, how investors manage existing stocks could explain the equilibrium vacancy and delays in supply responses. Conversely, high occupancy rates generally translate into high tenancy demand (Figure 2). Thus, tenants are less likely to negotiate a lease with office investors who have irrational or unreasonable preferences. In summary, I conjecture that biased investors mainly drive equilibrium vacancy and delays of supply responses.

In light of this, I transform the responses of CRE investors with overconfidence bias and disposition effects into the corresponding equilibrium vacancy and supply responsiveness.

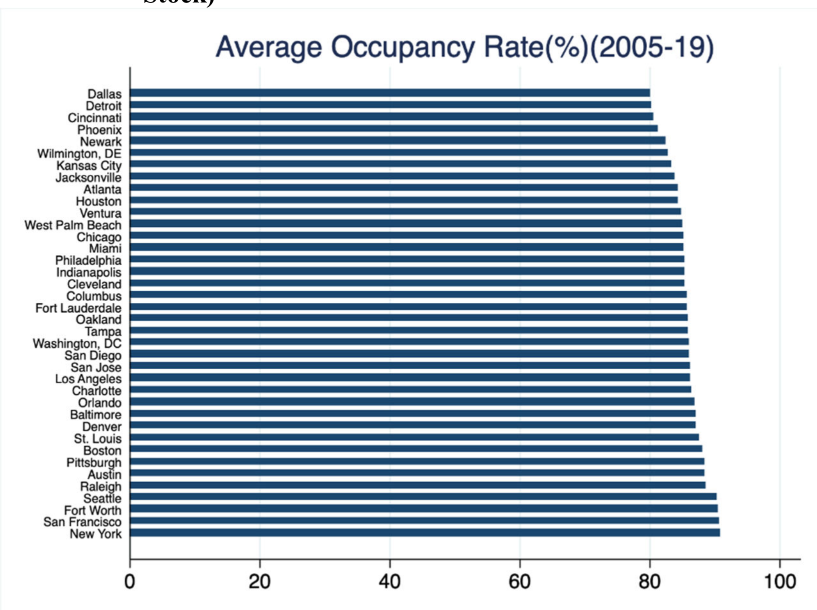
[2] Tax rates: Washington DC - 5% of the assessed value; New York State - 1%; San Francisco (per street facing foot) - $250 (2021), $250 or $500 (2022), $250, $500 or $1000 (2023); Los Angeles - $5000 per parcel; Oakland - $6000 per parcel.

Figure 1 New Office Completions in 38 MSAs (Percentage of Total Stock)



Source: CBRE Econometric Advisors

Figure 2 Average Occupancy Rate in 38 MSAs (Percentage of Total Stock)



Source: CBRE Econometric Advisors

2.2 Deriving Equilibrium Vacancy due to Overconfidence Bias

Rejecting the sublease option and alternatively seeking tenants for a direct lease are an aggressive strategy, since CRE investors forgo secure rental income.[3] This strategy can identify confident and overconfident investors: it is assumed that the latter fail to seek direct tenants. They set the asking rents based on their expectations and the number of potential tenants who are financially able to afford the rent level. Considering their risk aversion level (α) and overconfidence level (γ), the expectation of rent (Equation (1)) is composed of the market fundamental (R^f), risk premium ($RP(\alpha)$), forecasts of overconfident investors on deviation from the fundamental due to shock (i.e. rent volatility due to shock with the randomness on fundamental [$\sigma_{RS}\gamma * dZ_t^f$]), and other noises due to shock expected by overconfident investors, which correlate with the fundamental (i.e. other correlated noises on rent volatility, with the randomness of overconfident investors [$\sigma_{RS}\sqrt{1-\gamma^2} * dZ_t^{OC}$]).

$$E(R_t^{OC}) = R_t^f + RP_t(\alpha) + \sigma_{RS}\gamma * dZ_t^f + \sigma_{RS}\sqrt{1-\gamma^2} * dZ_t^{OC} \quad (1)$$

The success rate is the probability of reaching potential tenants for a deal, and the failure rate is (1 - success rate). The failure rate is interpreted as equilibrium vacancy due to the overconfidence bias (V^{OC})[Equation (2)]. The probability depends on whether the financial budget of potential tenants (TFB) exceeds the rent expectations of overconfident investors.

$$V_t^{OC} = 1 - Prob[E(R_t^{OC}) \leq TFB_t] \quad (2)$$

2.3 Deriving Equilibrium Vacancy due to Disposition Effect

Intuitively, investors with a tendency towards disposition hold significantly depreciated properties (i.e. a reduction in the value of an asset over time, due in particular to wear and tear) for longer than rational investors. There are two possible ways to exit: (1) realize loss by disposal and (2) upgrade property from a non-prime to a prime level. Only the second option can affect real estate supply; therefore, the conceptual framework only describes this path. For the disposition effect, even if the prime vs non-prime rental gap is sufficiently large enough to cover RCs, irrational investors will still hesitate to upgrade their significantly depreciated properties. Generally, rental income growth is technically described by using Equation (3) (where RE means the end of renovation). The result depends on the difference between the product of prime rent (Rp) and prime class occupancy (1-VP), after deducting RC and the product of non-prime rent (Rnp) and non-prime class occupancy (1-VNP):

[3] A real estate lawyer, Manley (1988), shared in the *Harvard Business Review* that investors may insist on taking back the space their tenants want to sublease, and negotiate a longer term with another tenant for a better deal in a boom period.

$$rg_t = \int_{RE}^{\infty} (1 - VP_t) R_p e^{-rt} dt - RC_t - \int_{0}^{\infty} (1 - VNP_t) R_{np} e^{-rt} dt \quad (3)$$

Following Kahneman and Tversky (1979) and Tversky and Kahneman (1992), I use the prospect theory value function $V(rg_t)$ to estimate the perceived value of rental income growth (rg_t) with the setup parameters of a tendency toward disposition (i.e., more tendency, lower β, $0 < \beta \leq 1$) and loss aversion (i.e. more averse, higher λ, $\lambda \geq 1$).

$$V(rg_t) = \begin{cases} rg_t^{\beta} & if\ rg_t \geq 0 \\ -\lambda(-rg_t)^{\beta} & if\ rg_t < 0 \end{cases}$$

Theoretically, equilibrium vacancy due to the disposition effect is measured by the probability of whether the perceived value of negative rental income growth is higher than that of positive rental income growth:

$$V_t^{DIS} = Prob[E(-\lambda(-rg_t)^{\beta}) > E(rg_t^{\beta}) \quad (4)$$

2.4 Supply Responsiveness due to Overconfidence Bias and Disposition Effect

In equilibrium, demand equals adjusted supply. The adjustment is the deduction of equilibrium vacant space from the total supply.[4] I classify equilibrium vacancy into four types: (1) due to overconfidence bias (V^{OC}), (2) due to disposition effect (V^{DIS}), (3) structural due to rational factors (V^{SRA}), and (4) frictional (V^{F}). The first two are derived in the above subsections, and the latter two from the conceptual model in Marcato and Tong (2023). The structural type due to rational factors comes from a search and matching process, and the net business survival of new firms drives the frictional type of vacancy.[5] The equilibrium state is described by using:

$$D = (1 - V^{OC})(1 - V^{DIS})(1 - V^{SRA})(1 - V^{F})S \quad (5)$$

To calculate supply responsiveness, which is generally measured by supply elasticity, I take the first derivative of Equation (5) with respect to rent (R) and multiply with $\frac{R}{S}$:

[4] Equilibrium vacancy can be interpreted as natural vacancy. However, there is a lack of literature that effectively explains the causes of natural vacancy (Voith and Crone, 1988; Grenadier, 1995; Sivitanides, 1997). My concept of distinguishing rational and irrational factors also aims to shed new light on this traditional view.

[5] Rental market friction is intuitively lower than sale market friction. In general, commercial lease law is less restrictive and emphasizes negotiation between both parties; therefore, the friction due to regulations should be lower. Also, investors pay property and corporate taxes, and commission fees for rental businesses; all of these costs are much lower than capital gain taxes and stamp duty on property acquisitions or disposal.

$$\frac{dD}{dR} = -\frac{dV^{OC}}{dR}(1-V^{F})(1-V^{DIS})(1-V^{SRA})S - \frac{dV^{DIS}}{dR}(1-V^{OC})(1-V^{SRA})(1-V^{F})S - \frac{dV^{SRA}}{dR}(1-V^{OC})(1-V^{DIS})(1-V^{F})S - \frac{dV^{F}}{dR}(1-V^{OC})(1-V^{DIS})(1-V^{SRA})S + \frac{dS}{dR}(1-V^{OC})(1-V^{DIS})(1-V^{SRA})(1-V^{F})$$

$$\begin{aligned}(1-V^{OC})(1-V^{DIS})(1-V^{SRA})(1-V^{F})\frac{R}{S}\frac{dS}{dR} &= (1-V^{OC})(1-V^{DIS})(1-V^{SRA})(1-V^{F})\frac{R}{D}\frac{dD}{dR} \\ &+ \frac{dV^{OC}}{dR}(1-V^{F})(1-V^{DIS})(1-V^{SRA})R \\ &+ \frac{dV^{DIS}}{dR}(1-V^{OC})(1-V^{SRA})(1-V^{F})R \\ &+ \frac{dV^{SRA}}{dR}(1-V^{OC})(1-V^{DIS})(1-V^{F})R \\ &+ \frac{dV^{F}}{dR}(1-V^{OC})(1-V^{DIS})(1-V^{SRA})R\end{aligned} \tag{6}$$

For supply responsiveness due to overconfidence bias, I divide the overall supply responsiveness equation (Equation (6)) by $(1-V^{DIS})(1-V^{SRA})(1-V^{F})$ to obtain:

$$(1-V^{OC})\frac{R}{S}\frac{dS}{dR} = (1-V^{OC})\frac{R}{D}\frac{dD}{dR} + R\frac{dV^{OC}}{dR} + \frac{R(1-V^{OC})}{(1-V^{DIS})}\frac{dV^{DIS}}{dR} + \frac{R(1-V^{OC})}{(1-V^{SRA})}\frac{dV^{SRA}}{dR} + \frac{R(1-V^{OC})}{(1-V^{F})}\frac{dV^{F}}{dR} \tag{7}$$

For supply responsiveness due to the disposition effect, I divide the overall supply responsiveness equation (Equation (6)) by $(1-V^{OC})(1-V^{SRA})(1-V^{F})$ to obtain:

$$(1-V^{DIS})\frac{R}{S}\frac{dS}{dR} = (1-V^{DIS})\frac{R}{D}\frac{dD}{dR} + \frac{R(1-V^{DIS})}{(1-V^{OC})}\frac{dV^{OC}}{dR} + R\frac{dV^{DIS}}{dR} + \frac{R(1-V^{DIS})}{(1-V^{SRA})}\frac{dV^{SRA}}{dR} + \frac{R(1-V^{DIS})}{(1-V^{F})}\frac{dV^{F}}{dR} \tag{8}$$

If overconfidence bias, the disposition effect, and market friction are not very rent sensitive, supply responsiveness due to overconfidence bias and the disposition effect is mainly determined by their respective impact on rational factors, including demand elasticity and structural vacancy due to the rational factor at equilibrium.

2.5 Conceptual Framework on Market Friction

In this study, market friction is distinguished from irrational biases. Friction arises from structural impediments such as regulation, land constraints, and tenant turnover from business entry and exit (Marcato and Tong 2023). In contrast, irrational biases reflect behavioral distortions in decision-making. I operationalize friction through measures of regulatory constraints, undevelopable land and net firm survival, while biases are captured by using overconfidence and disposition indicators. Supply responsiveness and equilibrium vacancy are thus decomposed into components attributable to rational frictions and irrational behaviors, which allow us to disentangle the two effects empirically.

3. Empirical Strategy

3.1 Innovative Approach to Identify Overconfidence Bias and Disposition Effect

In this study, I argue that some irrational biases are self-recognized, while some are unintentional. Therefore, traditional psychological tests based on the perceptions of respondents may not effectively evaluate the extent of unintentional irrational biases. Since irrational tendencies can be latent or hidden, I propose an innovative approach by observing relatively routine operating decisions to identify unintentional overconfidence bias and the relatively self-perceived disposition effect of CRE investors. This approach can help to detect irrationality more accurately when there are limited sales transactions in capital markets.

3.1.1 Overconfidence Bias

Typically, real estate investors can decide whether they allow tenants to sublease their already rented space. If subleasing is permitted, the investors will have a more secure and stable operating income flow, even though their direct tenants may face financial instability in the future. If tenants are not allowed to sublet, the investors may face a more significant loss due to the risk of bankruptcy of their tenants and the time needed to find other tenants for a direct lease. In other words, the preference for only direct leases (i.e., subleases are not allowed) is an aggressive operating decision, which shows the confidence of the investors in finding direct tenants for longer-term leases. Therefore, I examine direct- and sub-lease situations in each office market.

To further distinguish between "confident" and "overconfident" investors, I identify their failure in terms of whether they successfully reach a deal of direct leasing. A large number of available spaces for direct leasing in a market reflects the inability of investors; thus, the extent of overconfidence bias may be significant in specific markets.

To rule out possible failures due to a rational market downturn, I also compare the failure of tenants who want to sub-lease. Their price-taking behavior follows market trends when they seek sub-tenants. Thus, they are relatively rational (i.e., Assumption 1 below). The number of available spaces for subleasing indicates failure due to rational factors. The ratio of direct-to-sublease available space is used to quantify the relative strength of overconfidence bias in a market in general (i.e., Assumption 2 below).

Assumption 1: Tenants are relatively rational based on their price-taking behavior.

Assumption 2: The area with a more substantial overconfidence bias shows a larger ratio of direct-to-sublease available space.

3.1.2 Disposition Effect

Unlike stocks, which have mark to market prices with an apparent profit/loss, real estate is an inflation-hedging investor tool with an appraisal estimated value. However, it is very discernible that a property with significant depreciation would face a value reduction, as less rental income is received from a poor-quality property. In general, the disposition effect shows the willingness of an investor to realize investment loss. Therefore, I propose to observe how CRE investors decide to operate significantly depreciated properties (i.e., reducing value), in order to identify their disposition effect.

In the real estate market, there is more than one unique way to dispose of an asset (having a loss). Instead of simply selling out the acquisition, investors can choose to renovate significantly depreciated properties for an upgrade. Subsequently, the upgraded properties can generate prime rent. In the discounted cash flow approach, the upgraded properties would significantly rise in value. To identify the disposition tendency of investors and their loss aversion, I intuitively determine if they decide to renovate when the difference between the prime and non-prime rents is significant to cover RCs. If investors hesitate to renovate when the rental difference exceeds the market threshold, a disposition effect exists. In other words, the likelihood of a property upgrade according to the rental gap (whether it is larger than the threshold) decreases with the extent of the disposition effect (i.e., Assumption 3).

Assumption 3: In an area with a strong disposition effect, fewer property upgrades occur if the prime and non-prime rental gaps exceed the market threshold.

3.2 Disentangling Irrational Biases from Market Friction

Real estate capital markets are highly frictional, and the friction can distort investor behavior. For instance, fewer buyers are available to make large sale transactions, and hence even rational investors may not be able to sell out their assets. To shed light on market friction, I refer to Marcato and Tong (2023) to identify friction in office rental markets and measure equilibrium vacancy due to market friction in my empirical setup. Friction arises from net business survival, which leads to potential frequent leasing turnover. This approach can disentangle the effects of overconfidence bias and disposition from market frictions. Moreover, my analysis in a later section discusses how irrational biases and frictions reduce market liquidity, respectively.

3.3 Potential Endogeneity

To further clarify, the measure of overconfidence bias relies on the ratio of direct-to-sublet availability. Direct leasing without permission to sublease reflects investor confidence, while sublease failures capture rational tenant outcomes. By comparing the two, the ratio isolates overconfidence as the "excess failure" that cannot be explained by market conditions. Similarly, the disposition effect is proxied by the hesitation to renovate depreciated properties despite a prime-non-prime rental gap that exceeds RCs. This measure captures the unwillingness of investors to realize losses, which is consistent with the prospect theory.

While these measures could theoretically be endogenous if market-wide outcomes feed back into investor choices, I argue that the relative construction (direct rent vs sublease availability; upgrade decision conditional on rental gap) minimizes simultaneity concerns. Moreover, irrational behavior deviates responses to market conditions. That means the deviation reduces potential endogeneity. I choose lagged submarket vacancy differential and non-prime office stock share as the instrumental variables for overconfidence bias and the disposition effect, respectively, and subsequently conduct Hausman tests for endogeneity. The submarket vacancy differential influences the current decision of investors to allow sublets vs seeking to rent directly to tenants. As it is a lagged term, it is less likely to be contemporaneously driven by current shocks to supply responsiveness after controlling for fixed effects and controls. The share of non-prime office stock indicates older building stock which makes renovation decisions more salient and affects disposition tendency. Thus, the plausible exogenous structural feature is not driven by short-run rent swings. Table A1 in the Appendix summarizes the Hausman test results. The tests conclude that my measures of overconfidence bias and disposition effect can be treated as sufficiently exogenous for the empirical framework.

3.4 Empirical Model

First, I construct simultaneous equations of log(rent) (Equation (9)) and log(office supply) (Equation (10)) and obtain their reduced forms by using two stage least squares (2SLS). Since these two variables have non-stationary residuals at the level of the variables themselves (i.e., I(1)), a cointegration equation is formed in Engle-Granger error correction modeling. Although the model should consider the search and matching process in real estate market dynamics (Marcato and Tong 2023), the logarithm of the search effort level and mismatch rate having stationary residuals (i.e., I(0)) does not need to be endogenous in error correction modeling. Therefore, the equation of log(rent) contains an endogenous variable (i.e., log(office supply)), log(search effort level) (abbr. log(SEL)), log(mismatch rate) (abbr. log(MR)) and other exogenous variables (EXD) as demand drivers; these include undevelopable land area, a regulatory index, the growth of the ratio of employment in office-related sectors to population, and real income per capita and population indexes, where l and t denote MSA and time. The demand drivers are the control variables. I construct the equation of log(supply) by using the same procedure. EXS is a vector of the exogenous supply drivers (including overconfidence bias, disposition level, undevelopable land area, a regulatory index, market frictions, real operating expense growth, change in capitalization and Treasury yield gap, port city and travel time to work dummies). Except for the bias measures, exogenous supply drivers are the control variables used in the equation of log(supply). Based on the stationarity tests, all the time varying exogenous demand and supply drivers are I(0), including overconfidence bias. Other cross sectional variables including the disposition effect, undevelopable land area and the regulatory index do not introduce spurious regression effects with the I(1) variables. Therefore, the error correction models include them as EXD.

$$\begin{aligned} log(rent_{l,t}) = a_0 + a_1 log(supply_{l,t}) + a_2 log(SEL_{l,t}) \\ + a_3 log(MR_{l,t}) + a_4 EXD_{l,t} + \mu_{l,t}^{rent} \end{aligned} \tag{9}$$

$$\begin{aligned} log(supply_{l,t}) = b_0 + b_1 log(rent_{l,t}) + b_2 log(SEL_{l,t}) \\ + b_3 log(MR_{l,t}) + b_4 EXS_{l,t} + \mu_{l,t}^{supply} \end{aligned} \tag{10}$$

The reduced forms are used to construct a cointegration equation in the Engle-Granger approach. Due to simultaneity, I create two versions of the cointegration equation: (1) demand-side and (2) supply-side. By substituting the predicted value $log(\widehat{supply}_{l,t})$ into Equation (9), the demand-side cointegration equation helps to estimate demand elasticity, which can show whether tenants are rational. Rational tenants intuitively lead to elastic demand (i.e., they are more sensitive to market rents). Substituting the predicted value $log(\widehat{rent}_{l,t})$ into Equation (10) forms the supply-side cointegration equation (Equation (11)). To estimate supply responsiveness due to overconfidence bias, disposition level, regulations, and geographical barriers, I add related interaction terms to the equation and post-estimate the marginal effects based on the condition of each MSA. To estimate equilibrium vacancy driven by overconfidence, disposition effect, and market frictions, I take the exponential of $\left[c_2 log\left(\widehat{rent_{l,t}}\right) * overconfidence_{l,t} + c_6 overconfidence_{l,t}\right]$, $\left[c_3 log\left(\widehat{rent_{l,t}}\right) * disposition_{l,t} + c_7 disposition_{l,t}\right]$ and $\left[c_8 friction_{l,t}\right]$ respectively, and divide them by supply.

$$
\begin{aligned}
log\left(supply_{l,t}\right) = c_0 + c_1 log\left(\widehat{rent_{l,t}}\right) + c_2 log\left(\widehat{rent_{l,t}}\right) \\
* overconfidence_{l,t} + c_3 log\left(\widehat{rent_{l,t}}\right) \\
* disposition_{l,t} + c_4 log\left(\widehat{rent_{l,t}}\right) * regulation_l \\
+ c_5 log\left(\widehat{rent_{l,t}}\right) * nbarrier_l \\
+ c_6 overconfidence_{l,t} + c_7 disposition_{l,t} \\
+ c_8 friction_{l,t} + c_9 log\left(SEL_{l,t}\right) + c_{10} log\left(MR_{l,t}\right) \\
+ c_{11} EXS_{l,t} + \epsilon_{l,t}
\end{aligned} \tag{11}
$$

The error correction model can estimate short-run disequilibrium. I confirm the stability of short-run dynamics based on a negative error correction term in all of my models.[6] Due to a negligible interest in short-run disequilibrium, I only report the rate of adjustment.

In summary, the Engle-Granger panel-based error correction model is implemented in three steps. First, simultaneous equations for rents and supply are estimated by using 2SLS to mitigate simultaneity bias. Second, reduced forms are constructed to identify the long-run cointegrating relationship. Finally, the residuals are incorporated into an error correction model, where the coefficient on the lagged residual captures the rate of adjustment back to equilibrium. Short-run deviations are thus interpreted as transitory mismatches between supply and demand, while long-run coefficients capture the equilibrium effects of biases, frictions, and regulations. The inclusion of time dummies and exogenous controls (e.g. macroeconomic drivers, geographic constraints) ensures the robustness of the equilibrium interpretation.

3.5 Variable Definition and Descriptive Statistics

I obtain data from various sources and consider the relevant variables. Table 1 provides the definitions and compilation methods for all of the variables.

Table 2 summarizes the overall condition of irrational biases in the 38 MSAs from 2005Q1 to 2019Q4. The coverage accounts for 44% of the US population and 61% of the office workforce. After a preliminary examination of the irrational effects, I divide the entire sample into two sub-panels: (1) high vs (2) low overconfidence or disposition level. In general, higher overconfidence is shown in relatively small office markets. In contrast, a stronger disposition effect is present in mega office markets. However, there is no robust opposite

[6] Except for two demand-side short-run models in the robustness tests.

relationship between overconfidence bias and the disposition effect - moderately lower disposition effect (overconfidence) in an area with high overconfidence (disposition effect). As expected, market friction regarding new firm births and deaths are relatively constant across areas with different degrees of overconfidence bias and disposition effects.

Table 1 Variable Definitions

Variable	Description	Source
Real Rent Index	Nominal rent is based on the "total consideration" of the lease, or the non-discounted sum of all rental payments. These payments take into account any periods of free rent and any step increases but exclude taxes and cost-of-living increases, and any tenant improvements. Over 200,000 office leases are used to compile MSA-level market rent by the CBRE. The index is then statistically adjusted for the type of building, location, and lease term. I deflate the nominal index with CPI to compile the real rent index.	CBRE-EA
Office Stock	Total stock is classified into the prime (Class A) and non-prime (Classes B and C) stocks.	CBRE-EA
Search Effort Level	Employing the same approach as Marcato and Tong (2023), the difference between the maximum number of buildings in which asking rents are reported to the CBRE from 2015Q4 to 2019Q4 and the current number of reports, divided by the difference between the maximum and the minimum number of reports from 2015Q3 to 2019Q3. It is assumed that search effort decreases with the number of listings.	M & T, CBRE-EA
Economic Mismatch	This indicates a preference of landlords to lease the property to new tenants, instead of existing tenants who do not renew the contract with the newly requested amount. It is identified by the rate of occupied available space.	CBRE-EA
Mismatch Rate	In my main model, mismatch rate means the ratio of occupied available space to office stock. The alternative measure is suggested as the ratio of occupied available space to vacant stock, for the robustness test.	CBRE-EA
Overconfidence Bias	In my main model, overconfidence bias is identified by the direct-to-sublet availability ratio. The decision to reject sublet permission leads to less-secure rental income flow for investors who choose to seek direct leases. This decision-making reflects the confidence or overconfidence of investors. Since overconfidence is predicted with failure, direct available space (indicating that investors have not successfully found direct tenants) can identify the failure of	CBRE-EA

(Continued…)

(Table 1 Continued)

Variable	Description	Source
Overconfidence Bias	overconfident investors. However, sometimes their failure may be caused by market factors. Therefore, subletting available space (i.e., failure of rational tenants) is also considered to measure the relative strength of overconfidence to rational failure. In the robustness test, an alternative measure is suggested: the direct-to-sublet vacancy ratio. Only already vacant space is considered.	CBRE-EA
Disposition Effect	Real estate with great depreciation value is treated as an asset with reducing value due to wear and tear. Investors who have a tendency toward disposition hesitate to renovate for an upgrade, even if the rental gap between prime and non-prime offices is larger than the rational market threshold. I check to see if there is property being upgraded (from non-rentable and non-prime offices to new prime offices) when the mentioned rental gap exceeds 40% (main analysis) and 50% (robustness test). The thresholds are set based on Marcato and Tong (2023). Then, I apply a logistic model for each MSA to estimate the odds ratios which are interpreted as the likelihood of upgrade driven by the rental gap dummy. More than 65% of the estimates are significant at the 10% level for a 40% rental gap (76% for a 50% rental gap). The strength of the disposition tendency decreases with the upgrade likelihood; therefore I calculate the level of disposition as [100/(1+odds ratio)].	M&T, CBRE-EA
Market Friction	Frictions in office markets arise from a potential frequent turnover of new business startups and failures. New firms take more time to find the most suitable location for their business, and therefore decide to move more frequently than well-established companies. Their move causes friction in rental markets that are identified by net business survival [i.e. new firm births and deaths] (Marcato and Tong 2023).	BDS
UDA	Saiz (2010) estimates the area within a 50-kilometer radii of cities corresponding to wetlands, lakes, rivers, or other internal water bodies to quantify land availability.	Saiz
Wharton Regulatory Index	The original index was compiled based on large-scale surveys of the planning approval process that measured the stringency of regulatory supply constraints (Gyourko et al. 2008). A new survey was conducted in 2018 for re-compilation.	WRI
Port City	A dummy to indicate whether an MSA has a port.	CS

(Continued…)

(Table 1 Continued)

Variable	Description	Source
TTWD	TTWD identifies whether a MSA lacks transportation. If residents requires more than the MSA average commuting time, the transportation infrastructure is regarded as insufficient.	CS
EMPG	The employment covers the office-using sectors, including finance and professional services.	CBRE-EA
RIPCG	The growth of real income per capita is chosen as one of the office demand drivers.	CBRE-EA
POPIG	I set the base at (2015=100) to compile the index and its growth.	CBRE-EA
ROPEXG	I deflate nominal operating expense (i.e. gross income – net operating income – tax) with consumer price index (CPI).	CBRE-EA
CTG	An indicator of the riskiness of office markets that can be considered exogenous because of the mispricing risk of the credit market (Wachter, 2016).	CBRE-EA, FRB

Notes: This table provides the definitions, compilation methods, and sources of variables used in my study. CBRE Econometric Advisors – CBRE-EA; Marcato and Tong (2023) – M&T; the Business Dynamics Statistics from US Census – BDS; Saiz (2010) – Saiz; Wharton Residential Land Use Regulatory Index (Gyourko et al., 2008; Gyourko and Krimmel, 2021) – WRI; US Census – CS; Federal Reserve Board – FRB. Undevelopable Land Area – UDA; Travel Time to Work – TTWD; Growth of Employment in Office Using Sectors to Population – EMPG; Growth of Real Personal Income per Capita – RIPCG; Population Index Growth – POPIG; Real Operating Expense Growth – ROPEXG; and Change in Capitalization – Treasury Yield Gap – CTG.

The geographical distributions of the disposition effect and overconfidence bias are exhibited in Figure 3 where for the disposition level, the figure is based on calculations of the likelihood of property upgrade when the prime vs non-prime rental gap exceeds 40%. Regarding the overconfidence bias, Figure 3 represents the ratio of available direct-to-sublet space. Availability means that the investors or tenants fail to find new tenants or sub-tenants. The ratio indicates the relative strength of overconfidence bias. In terms of the disposition effect indicated by the reversal likelihood of property upgrade in the condition where the prime vs non-prime rental gap exceeds 40%,[7] Orlando and Washington, DC have the most substantial disposition effect, while Raleigh and Columbus have the lowest. For overconfidence bias measured by the ratio of available direct-to-sublet space, Detroit has the highest overconfidence bias, whereas San Francisco has the least overconfidence bias. This phenomenon may be caused by less transparent market information in relatively small markets.

[7] The threshold is set based on industry information (Marcato and Tong 2023).

Table 2 Data Summary Statistics

		All		Overconfidence				Disposition			
				High		Low		High		Low	
Abbreviation	**Variable**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
$RRI_{l,t}$	(a)*Real Rent Index (2015Q4=100)	101.163	11.901	100.556	10.144	101.540	12.861	101.640	12.035	100.686	11.752
$S_{l,t}$	(a)*Office Stock (mil sqf)	85.683	89.566	50.061	33.804	107.786	104.965	114.956	110.393	56.411	46.360
$SEL_{l,t}$	*Search Effort Level (%)	30.761	30.754	27.999	29.969	32.475	31.118	30.663	28.618	30.860	32.763
$EMM_{l,t}$	Economic Mismatch (mil sqf)	4.346	4.717	2.417	1.926	5.544	5.479	5.997	5.671	2.696	2.629
$MR_{l,t}$	*Mismatch Rate (%)	4.865	1.606	4.685	1.546	4.977	1.632	5.140	1.645	4.591	1.517
$MR^*_{l,t}$	*Mismatch Rate (%) - Alternative	36.143	16.466	31.716	14.784	38.890	16.859	36.393	14.270	35.893	18.405
$DSUBA_{l,t}$	Direct to Sublet Availability Ratio (%)	10.093	5.481	15.113	5.604	6.979	1.965	9.504	5.229	10.682	5.663
$DSUBV_{l,t}$	Direct to Sublet Vacancy Ratio (%)	21.625	28.303	35.236	41.095	13.210	8.214	20.261	19.881	22.994	34.712
$DVAC_{l,t}$	Direct Vacancy (mil sqf)	10.984	10.031	7.864	6.255	12.920	11.360	14.576	11.323	7.392	6.878
$SLVAC_{l,t}$	Sublet Vacancy (mil sqf)	0.944	1.320	0.314	0.292	1.335	1.541	1.334	1.644	0.555	0.694
$DVAS_{l,t}$	Direct Availability (mil sqf)	14.293	13.291	9.846	7.503	17.052	15.216	19.103	15.218	9.483	8.693
$SLAVS_{l,t}$	Sublet Availability (mil sqf)	1.982	2.491	0.749	0.685	2.748	2.870	2.805	3.083	1.160	1.249

(Continued…)

(Table 2 Continued)

		All		Overconfidence				Disposition			
				High		Low		High		Low	
Abbreviation	**Variable**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
$PUP_{l,t}$	Property Upgrade Dummy	0.523	0.500	0.538	0.499	0.514	0.500	0.536	0.499	0.511	0.500
$NRG40_{l,t}$	Prime vs Non-Prime Net Asking Rental Gap ≥ 40%	0.346	0.476	0.368	0.482	0.332	0.471	0.377	0.485	0.314	0.464
$NRG50_{l,t}$	Prime vs Non-Prime Net Asking Rental Gap ≥ 50%	0.265	0.441	0.297	0.457	0.245	0.430	0.281	0.450	0.249	0.433
$DIS40_{l}$	(b) Disposition Level (%)	31.267	11.699	29.672	12.444	32.260	11.103	40.600	7.187	21.935	6.920
$DIS50_{l}$	(b) Disposition Level (%) – Alternative	26.288	12.206	26.192	12.360	26.347	12.114	35.286	8.165	17.289	8.329
$NFB_{l,t}$	(c) New Firm Birth (%)	12.976	2.418	12.586	2.730	13.218	2.168	12.940	2.473	13.012	2.361
$NFD_{l,t}$	(c) New Firm Death (%)	3.543	1.084	3.196	1.033	3.758	1.059	3.486	1.048	3.600	1.116
UDA_{l}	Undevelopable Land Area (%)	31.175	24.491	27.363	24.442	33.540	24.230	26.586	22.664	35.764	25.384
$WRI08_{l}$	Wharton Land Regulatory Index (2008)	-0.293	0.567	-0.079	0,576	-0.426	0.519	-0.387	0.630	-0.198	0.478
$WRI18_{l}$	Wharton Land Regulatory Index (2018)	-0.384	0.504	-0.187	0.484	-0.507	0.478	-0.448	0.459	-0.320	-0.538
$PORT_{l}$	Port City	0.421	0.494	0.395	0.489	0.437	0.496	0.368	0.483	0.474	0.500

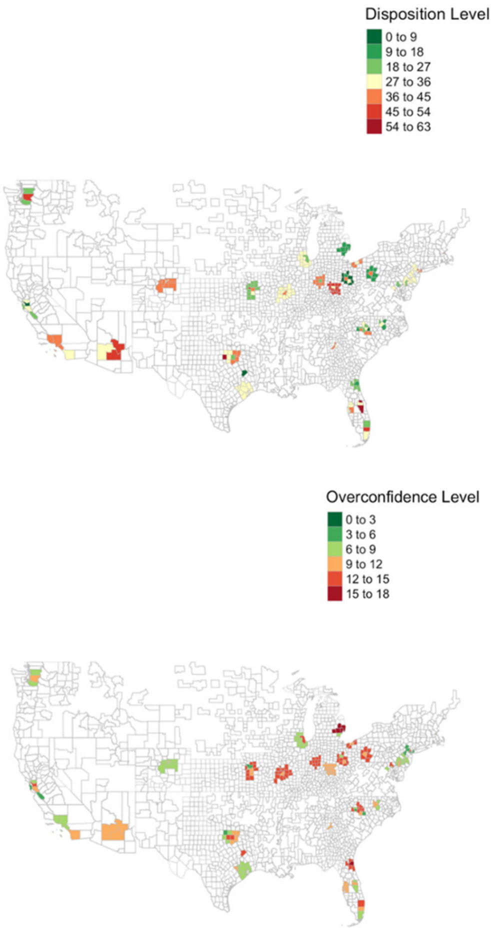
(Continued…)

(Table 2 Continued)

		All		Overconfidence				Disposition			
				High		Low		High		Low	
Abbreviation	**Variable**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
$TTWD_l$	Travel Time to Work Dummy	0.342	0.475	0.123	0.328	0.478	0.500	0.421	0.494	0.263	0.441
$EMPG_{l,t}$	Growth of Employment in Office Using Sectors to Population	-0.041	0.406	-0.097	0.357	-0.005	0.429	-0.013	0.371	-0.068	0.437
$RIPCG_{l,t}$	Growth of Real Personal Income per Capita	0.070	0.355	0.099	0.354	0.053	0.354	0.068	0.326	0.073	0.381
$POPIG_{l,t}$	Population Index Growth	0.059	0.052	0.052	0.047	0.064	0.054	0.059	0.050	0.060	0.053
$ROPEXG_{l,t}$	Real Operating Expense Growth	-0.012	0.523	-0.070	0.413	0.024	0.578	0.008	0.429	-0.032	0.602
$CTG_{l,t}$	Change in Capitalization-T Yield Gap	0.005	0.612	-0.0004	0.136	0.009	0.772	0.0001	0.818	0.011	0.284
	Observation	2280		873		1407		1140		1140	

Notes: All statistics (except specified) are based on a sample of 38 MSAs from 2005Q1 to 2019Q4 for each variable. The panel is divided by the degree of overconfidence and disposition level. The classification is based on the direct-to-sublet availability ratio and disposition level (DIS40) respectively. A high (low) disposition level means the extent that is above (below) average. (a) Their logarithm is I(1) (i.e. non-stationary residual in the disposition level) and therefore Engle-Granger approach error correction modeling is adopted. (b) DIS40 and DIS50 are calculated based on a rental gap that is larger than 40% and 50% respectively. Since property upgrades and the rental gap are observed at the MSA level on a quarterly basis, the estimates of the disposition level are an average over time. (c) annual basis. * indicates endogenous variables, but log(search effort level) and log(mismatch rate) are I(0) (i.e. stationary residual). Therefore, only one cointegration equation is formed.

Figure 3 Estimated Disposition Level and Overconfidence Level in 38 MSAs (Author Estimates)



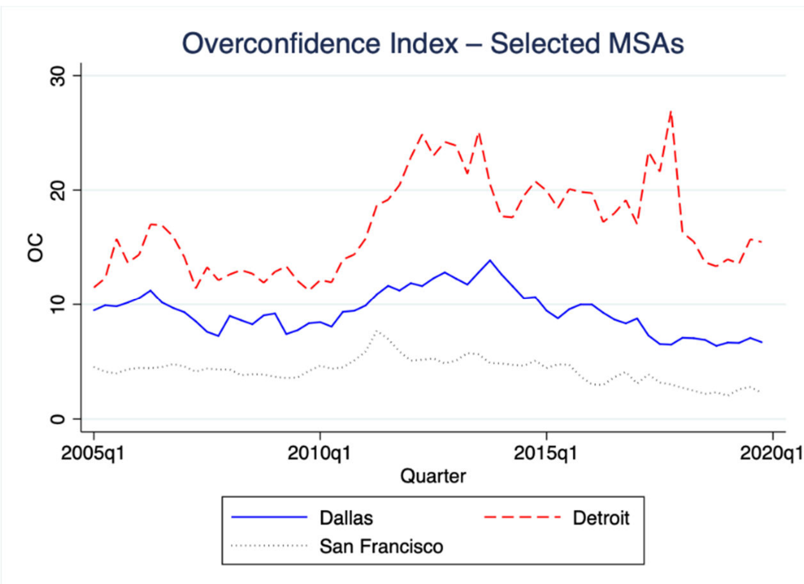
Unlike overconfidence, which is proxied by quarterly leasing outcomes and therefore time-varying (Figure 4), the disposition effect is measured as an MSA-level structural parameter. Specifically, I estimate the odds of property upgrade conditional on the prime-non-prime rental gap that exceeds the renovation threshold, and then invert this to construct a disposition index. Since upgrades are relatively infrequent events, the odds ratios are estimated over the full sample, which makes the disposition measure essentially cross-sectional. It should thus be interpreted as a persistent market characteristic rather than a short-run fluctuation. Based on the average overconfidence level from 2005 to 2019, San Francisco and Detroit have the lowest and highest overconfidence levels respectively, and the overconfidence bias of Dallas is at the median level across the MSAs.

3.6 Interpretation of Biased MSAs

The geographical variation in the biases reflects the underlying market characteristics. For example, Detroit and Indianapolis exhibit high overconfidence bias, consistent with smaller and less transparent markets where investors rely heavily on private forecasts. San Francisco and San Jose exhibit the least overconfidence bias, consistent with their highly analytical developer base, volatile demand cycles, and stringent regulatory environments that discourage excessively optimistic supply decisions. Orlando and Washington DC, in contrast, show strong disposition effects, likely due to a combination of older building stock and regulatory hurdles that amplify investor hesitation to renovate. Columbus and Raleigh show the smallest disposition effect, likely reflecting their young building stock, high population inflow, and flexible pro-development institutions that reduce sunk-cost attachment and facilitate timely adjustment to market conditions. These local contexts suggest that biases are shaped by both behavioral tendencies and structural market features.

An important distinction between the two measures is their time dimension. The overconfidence index is constructed quarterly, thus reflecting the changing availability conditions in direct versus sublet leases, and therefore captures cyclical variation in investor sentiment. By contrast, the disposition effect is identified from the average upgrade behavior of investors relative to the rental gap over the sample window. It is treated as a cross-sectional attribute of each MSA, thus representing the long-run tendency of investors to hesitate in upgrading depreciated properties.

Figure 4 Estimated Overconfidence Level in Selected MSAs over Time



4. Main Results and Analysis

4.1 Tenants are Rational

In this section, I first show the overall rationality of tenants, which helps to emphasize the irrational effects driven by real estate investors. As mentioned in Assumption 1, rational tenants are inclined to be price takers in rental markets. In other words, their demand is susceptible to rents, given that searching costs and lease terms are controlled. Thus, I hypothesize that rational tenants cause demand to be elastic. Table 3 reports the results of the demand-side cointegration equation. Whether the model includes time dummies or the regulatory constraints may vary, the demand elasticity (i.e., the reciprocal of the coefficient of log(supply)) is significantly high. The finding confirms that the tenants in my sample markets are inclined to be rational. Therefore, the confirmation supports the argument that the failure of tenants to sublease is due to rational factors. Hence, comparing the loss between irrational investors and rational tenants makes sense to quantify overconfidence bias.

Table 3 Tenants Tend to Be Rational

	(1)	(2)	(3)	(4)
log(Office Stock)	-0.031*** (0.004)	-0.040*** (0.004)	-0.026*** (0.004)	-0.034*** (0.004)
Demand Elasticity	-31.96***	-25.26***	-38.75***	-29.15***
Undevelopable Land Area	Y	Y	Y	Y
Wharton Land Regulatory Index				
2008	Y	Y	N	N
2008-18 Average	N	N	Y	Y
Time Dummies	N	Y	N	Y
Adjusted R-sq	0.24	0.31	0.24	0.31
Observation	1965	1965	1965	1965

Notes: It is hypothesized that rational tenants lead to elastic office demand given searching costs are controlled. I construct the reduced form of simultaneous equations and hence adopt the Engle-Granger approach to estimate the demand-side cointegration equation. The dependent variable is log(real rent index). log(mismatch rate) and log(search effort level) which are I(0) are included. Also, exogenous variables are included: growth of employment in the office using sectors to population, growth of real personal income per capita, population index growth, undevelopable land area, and Wharton land regulatory index (2008 or the average of the 2008 and 2018 versions). Demand elasticity is calculated as a reciprocal of the coefficient of office stock. The residual of each cointegration equation is stationary at the 10% significance level. ***, ** and * represent significant results at 1%, 5%, and 10% significance levels, respectively. The standard error is reported in parentheses.

4.2 Comparing Impacts of Irrational, Regulatory and Geographical Supply Constraints

I include the corresponding variables in the supply-side cointegration equation in order to understand the effects of overconfidence bias and disposition on rentable office supply and compare their impact with those of regulations and geographical barriers. Table 4 presents twelve versions of the results. Models 1 to 4 exclude time dummies while Models 5 to 12 include time dummies. Generally, the results from the different models are consistent. Models 1, 5, and 9 do not have any interaction terms. Model 5 shows that regulations significantly impact supply, whereas overconfidence bias, disposition effect, and geographical barriers (i.e., undevelopable land area) do not. One unit of relaxation on restrictions leads to about a 0.1% increase in office supply. The second most significant impact comes from overconfidence bias - one unit increase in the extent of overconfidence in the area causes a slight reduction of 0.01% in the rentable supply. In addition, Model 9 confirms the impact of new firm births and deaths on office supply. Based on semielasticity, one unit increase in market frictions (i.e., a combination of new firm births and deaths) leads to about a 2% increase in supply. However, the supply produced by friction may not enhance market efficiency.

Without considering the interactions of real rent with the sources of supply constraints, Model 5 finds an inelastic supply (i.e., 0.789) which is consistent with the findings by Marcato and Tong (2023). Model 6, including the interaction terms of real rent with geographical and regulatory constraints, shows that supply responsiveness due to geographical barriers is much slower than regulations. However, the coefficient of real rent cannot be confirmed. Model 7, which considers interactions of real rent with overconfidence bias and disposition level, finds that supply responsiveness is slow due to overconfidence bias and disposition level (even reducing the rentable supply). In general, rational investors in any area would respond quickly to real rent (i.e., increase the supply by 2.304% in response to a 1% increase in real rent). Model 8, which incorporates all interactions, further confirms that the supply response to market rent is the slowest due to geographical barriers followed by overconfidence bias. Moreover, investors who have a tendency toward disposition would even reduce rentable supply when the market rent increases. Their hesitation to upgrade an obsolete office (i.e., an asset with reducing value) causes a smaller new rentable supply. Also, rational investors in the area without geographical barriers and regulatory issues increase the supply by 1.251% when real rent increases by 1%.

In Models 9 to 12, I replace the 2008 version of the Wharton regulatory index with the average of 2008 and 2018. The results are consistent with those from Models 5 to 8; however, the replaced regulatory index is not statistically significant in Model 12. This finding implies that the regulations remained the same from 2005 to 2017 (my sample period is 2005 to 2019).

4.3 MSA-Level Supply Responsiveness due to Disposition Effect, Overconfidence Bias, Regulation and Geographical Barriers

Table 5 presents the level of supply responsiveness due to investors with a tendency toward disposition (who are overconfident), regulations, and geographical barriers at the MSA level. The first and foremost finding is that disposition tendency of the investors plays a prominent role in causing the rentable office supply to be highly inelastic in each MSA, since its supply responsiveness is the slowest. Irrational factors are a crucial addition to conventional regulatory and geographical factors in determining supply responsiveness. Limited new supply enhances the influence of strategic management on existing supply. Therefore, the decisions of investors could significantly affect office supply dynamics.

Based on the extent of the overconfidence bias in each MSA, overconfident investors in 11 of the 38 MSAs may react relatively rationally when facing an increase in rent, and their supply elasticity ranges from 1.009 to 1.158. In most of the MSAs, overconfidence bias leads to an inelastic rentable supply. Compared with investors who have a tendency toward disposition, the aggregate behavior of overconfident investors deviates less from market norms. This finding may be due to a smaller number of overconfident investors relative to those inclined towards disposition.

As shown in Figure 5, the most significant disposition effect on supply responsiveness is found in Orlando, Washington DC, Cincinnati, and Phoenix. This finding is also supported by other statistics related to renovation, where 3.6%, 7%, 3.8%, and 1.7% of the office properties were fully renovated during 2000-2019, respectively[9]. Figure 5 also exhibits the geographical distribution of overconfidence bias. The supply responsiveness of overconfident investors is the slowest in New York, Newark, San Francisco, and San Jose, which implies that overconfident investors in mega markets are inclined to tightly control the rentable supply in the market. For instance, they may target specific high-profile tenants to reach direct leases for prime-quality offices. Detroit, West Palm Beach, and Ventura have the most responsive overconfident investors. These areas show another situation where overconfident investors rely heavily on their belief or forecast of boom markets, and hence invest in new development. Since the market sizes are relatively small, less information may be available for their projections.

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[9] The highest percentages of renovated offices are found in Manhattan (16%), Boston (10.8%), Bridgeport (9.4%), and San Francisco (9.1%). The statistics are sourced from CommercialCafe.

Table 4 Comparison of Significance of Irrational, Regulatory, and Geographical Supply Constraints

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)
log(Real Rent Index)	0.276 (0.317)	-0.665* (0.366)	2.097*** (0.480)	1.179** (0.579)	0.789** (0.390)	-0.211 (0.432)
log(Real Rent Index) x Undevelopable Land Area		0.032*** (0.006)		0.020*** (0.006)		0.032*** (0.006)
log(Real Rent Index) x Regulatory Index		1.110*** (0.313)		0.709** (0.314)		0.963*** (0.318)
log(Real Rent Index) x Overconfidence Bias			0.085*** (0.025)	0.087*** (0.025)		
log(Real Rent Index) x Disposition Level			-0.099*** (0.012)	-0.087*** (0.012)		
Undevelopable Land Area	-0.013*** (0.001)	-0.160*** (0.027)	-0.013*** (0.001)	-0.106*** (0.028)	-0.013*** (0.001)	-0.159*** (0.027)
Regulatory Index	0.236*** (0.031)	-4.862*** (1.441)	0.238*** (0.031)	-3.022** (1.448)	0.237*** (0.031)	-4.182*** (1.465)
Overconfidence Bias	-0.030*** (0.003)	-0.031*** (0.003)	-0.424*** (0.114)	-0.432*** (0.117)	-0.032*** (0.003)	-0.033*** (0.003)
Disposition Level	0.010*** (0.001)	0.010*** (0.001)	0.469*** (0.054)	0.414*** (0.057)	0.010*** (0.001)	0.009*** (0.001)
New Firm Birth	0.021*** (0.008)	0.021*** (0.008)	0.023*** (0.007)	0.023*** (0.007)	0.024** (0.010)	0.029*** (0.010)
New Firm Death	0.014 (0.023)	0.001 (0.023)	0.016 (0.023)	0.009 (0.023)	0.035 (0.028)	0.006 (0.028)
Wharton Regulatory Index						
2008	Y	Y	Y	Y	Y	Y
2008-18 Average	N	N	N	N	N	N
Time Dummies	N	N	N	N	Y	Y
Adjusted R-sq	0.52	0.53	0.54	0.54	0.52	0.53
Observation	1965	1965	1965	1965	1965	1965

(Continued…)

(Table 4 Continued)

Panel B

	(7)	(8)	(9)	(10)	(11)	(12)
log(Real Rent Index)	2.304*** (0.522)	1.251** (0.610)	0.468 (0.384)	-0.351 (0.420)	1.881*** (0.511)	1.079* (0.600)
log(Real Rent Index) x Undevelopable Land Area		0.022*** (0.006)		0.031*** (0.007)		0.020*** (0.007)
log(Real Rent Index) x Regulatory Index		0.657** (0.319)		0.902** (0.379)		0.506 (0.400)
log(Real Rent Index) x Overconfidence Bias	0.080*** (0.026)	0.084*** (0.026)			0.088*** (0.025)	0.087*** (0.027)
log(Real Rent Index) x Disposition Level	-0.090*** (0.012)	-0.077*** (0.013)			-0.089*** (0.012)	-0.078*** (0.012)
Undevelopable Land Area	-0.013*** (0.001)	-0.114*** (0.028)	-0.012*** (0.001)	-0.153*** (0.030)	-0.011*** (0.001)	-0.105*** (0.031)
Regulatory Index	0.239*** (0.031)	-2.778* (1.470)	0.500*** (0.039)	-3.647** (1.747)	0.500*** (0.038)	-2.100 (1.844)
Overconfidence Bias	-0.401*** (0.119)	-0.422*** (0.122)	-0.034*** (0.003)	-0.035*** (0.003)	-0.440*** (0.116)	-0.437*** (0.125)
Disposition Level	0.427*** (0.056)	0.367*** (0.059)	0.010*** (0.001)	0.010*** (0.001)	0.419*** (0.054)	0.372*** (0.057)
New Firm Birth	0.030*** (0.010)	0.033*** (0.010)	0.025** (0.010)	0.029*** (0.010)	0.031*** (0.010)	0.034*** (0.010)
New Firm Death	0.018 (0.028)	0.002 (0.028)	0.054** (0.027)	0.031 (0.027)	0.038 (0.027)	0.025 (0.027)
Wharton Regulatory Index						
2008	Y	Y	N	N	N	N
2008-18 Average	N	N	Y	Y	Y	Y
Time Dummies	Y	Y	Y	Y	Y	Y
Adjusted R-sq	0.54	0.54	0.55	0.56	0.56	0.57
Observation	1965	1965	1965	1965	1965	1965

Notes: The effects of overconfidence bias and disposition on office supply are determined and the significance with regulatory and geographical factors compared by estimating the Engle-Granger approach supply-side cointegration equation. To solve simultaneity, I construct the reduced form of simultaneous equations. The dependent variable is log(office stock). Overconfidence bias is quantified by the direct-to-sublet availability ratio (i.e. the strength of the overconfidence of investors relative to the failure of rational tenants). Disposition level is measured by the reverse of the likelihood of property upgrade where the prime vs non-prime net asking rental gap is larger than 40%. Regulatory stringency refers to the Wharton land regulatory index (i.e. larger number, less regulated) and geographical barriers are measured by undevelopable land area (Saiz 2010). To decompose the factors of constraints, interaction terms are applied. To measure market friction, each equation includes new firm birth and new firm death. log(mismatch rate) and log(search effort level) which are I(0) are included. Other exogenous variables are included: real operating expense growth, change in capitalization-T yield gap, and port city and travel time to work dummies. The residual of each cointegration equation is stationary at the 1% significance level. ***, ** and * represent significant results at the 1%, 5%, and 10% levels, respectively. The standard error is reported in parentheses.

Table 5 Supply Responsiveness Due to Disposition Effect, Overconfidence Bias, Regulations, and Geographical Barriers at MSA Level

MSA	Disposition Effect	Overconfidence Bias	Regulation	Geographical Barrier
Orlando	-4.642***	0.736***	-0.254	0.797***
Washington, DC	-3.956***	0.621***	-0.244	0.308***
Cincinnati	-3.859***	1.009***	0.364***	0.227**
Phoenix	-3.800***	0.875***	-0.465	0.308***
Atlanta	-3.301***	0.663***	-0.028**	0.090**
Fort Worth	-3.192***	0.823***	0.176**	0.108**
Boston	-3.153***	0.504***	-1.010	0.748***
Dallas	-3.126***	0.786***	0.219**	0.202**
Los Angeles	-3.035***	0.560***	-0.341	1.157***
Indianapolis	-3.033***	1.136***	0.498***	0.032**
Cleveland	-2.976***	1.104***	0.091**	0.893***
Denver	-2.937***	0.591***	-0.572	0.369***
New York	-2.885***	0.355***	-0.425	0.892***
Miami	-2.765***	0.832***	-0.512	1.690***
Baltimore	-2.754***	0.868***	-0.713	0.482***
Houston	-2.618***	0.641***	0.216**	0.185**
Philadelphia	-2.542***	0.642***	-0.676	0.224**
Newark	-2.495**	0.404***	-0.369	0.673***
Ventura	-2.470**	1.152***	-0.793	1.757***
Chicago	-2.400**	0.654***	-0.043**	0.883***
Tampa	-2.358**	0.804***	0.096**	0.919***

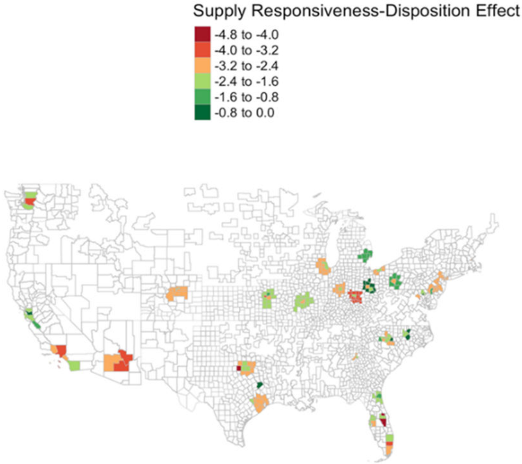
(Continued…)

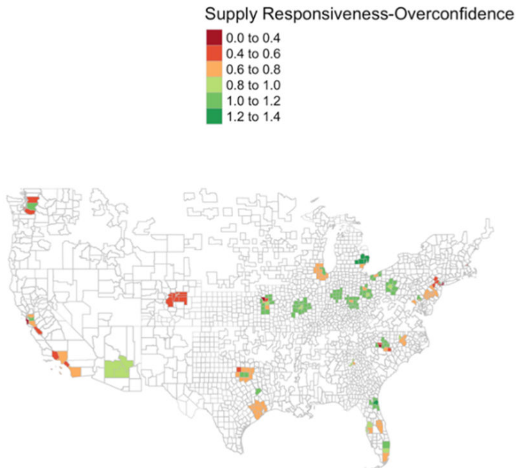
(Table 5 Continued)

MSA	Disposition Effect	Overconfidence Bias	Regulation	Geographical Barrier
San Diego	-2.173*	0.542***	-0.334	1.399***
St. Louis	-2.140*	1.139***	0.474***	0.244**
Charlotte	-2.105*	0.784***	0.279**	0.103**
Oakland	-2.105*	0.651***	-0.322	1.360***
Kansas City	-2.084*	1.134***	0.527***	0.128**
Wilmington, DE	-1.922	0.835***	-0.418	0.324***
Jacksonville	-1,896	1.130***	-0.010**	1.044***
Seattle	-1.893	0.514***	-0.647	0.962***
West Palm Beach	-1.877	1.158***	-0.204*	1.412***
San Francisco	-1.730	0.368***	-0.569	1.613***
San Jose	-1.598	0.471***	-0.116*	1.407***
Fort Lauderdale	-1.401	0.793***	-0.477	1.670***
Austin	-1.099	0.675***	-0.070*	0.083**
Detroit	-1.052	1.360***	-0.067*	0.541***
Pittsburgh	-0.858	1.095***	-0.044**	0.662***
Raleigh	-0.799	0.717***	-0.401	0.179**
Columbus	-0.680	1.056***	-0.131*	0.055**

Notes: Model 8 in Table 4 is used to post-estimate the marginal effects of rents to measure supply responsiveness to rents driven by the disposition effect, overconfidence bias, regulations, and geographical barriers based on the condition of each MSA. For overconfidence bias, the condition of overconfidence level is inputted into each MSA and zero for other factors, and so on. The supply responsiveness equals the subtraction of the coefficient of log(real rent index) in Model 8 from the coefficient of marginal effect. ***, ** and * represent significant results at the 1%, 5%, and 10% levels, respectively.

Figure 5 Supply Responsiveness due to Disposition Effect and Overconfidence Bias at MSA Level (Author Estimates)





4.4 How do Disposition Effect, Overconfidence Bias, and Market Friction Affect Market Illiquidity?

Another interesting discussion is related to the irrational effects on market illiquidity when irrational effects are in aggregate. Furthermore, comparing irrational factors with market friction in frictional real estate markets is crucial. In stock markets, illiquidity depends on systematic risk, trading volume, and primitive economic forces (Chordia et al., 2009). The typical stock pricing models created by Pástor and Stambaugh (2003) and Fama and French (2015) measure liquidity with volume signed by the contemporaneous stock return in excess of the market. Others may also consider the price impact of trade and bid-ask spreads (Baker and Stein, 2004). In short, the trading volume of stocks with an abnormal return indicates market liquidity. Gurun et al. (2016) use the time-on-market measure of market liquidity in housing markets. In other words, the number of tradable houses indicates market liquidity. In my analysis, I apply the same concept to measure real estate market illiquidity in the form of equilibrium vacancy due to the disposition effect, overconfidence bias, and market friction. This indicates that the space is not used in equilibrium (i.e., analogous to non-trading stocks). In this sense, there is always an illiquid portion of real estate markets.

Table 6 reports the MSA-level estimates of equilibrium vacancy driven by different factors. Column 1 shows equilibrium vacancy due to the disposition effect in the range of 0.460 to 6.727. As shown in Column 2, equilibrium vacancy due to overconfidence bias ranges from 0.262 to 7.470. In 21 of 36 MSAs, equilibrium vacancy due to the disposition effect is higher than that caused by the overconfidence bias. This finding implies that the disposition effect leads to higher market illiquidity in most cases; in other words, the disposition effect occurs more frequently than overconfidence bias. Moreover, the supply responsiveness of overconfident investors is highly correlated with related equilibrium vacancy (+0.63). This implies that inaccurate market forecasting of overconfident investors leads to overreaction (i.e. over-supply in a specific class of offices). Hence, their new rentable supply is not trading. Eventually, the market tends to be more illiquid.

Korniotis and Kumar (2011) examine the adverse effects of behavioral biases (including overconfidence, home bias, and speculation) on geographically varying income risk-sharing. Using the average portfolio turnover to proxy overconfidence, they find that overconfidence decreases with risk sharing. My evidence that vacant rentable supply in equilibrium is a consequence of the over-reaction of overconfident investors is in line with their findings. Clayton et al. (2008) show that the overconfidence bias of buyers (instead of sellers) stimulates market liquidity in real estate sales markets. Contributing to the related literature, I shed light on the role of overconfident office rental service sellers in determining market illiquidity.

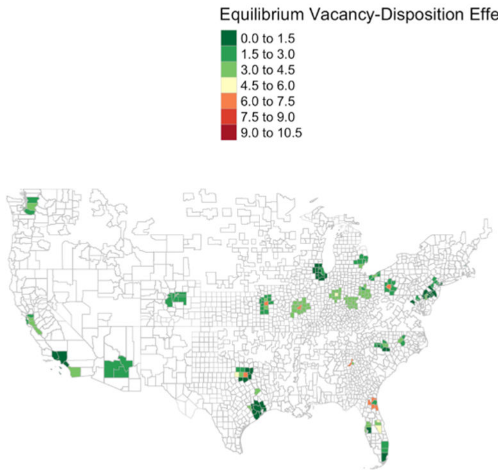
Since Model 8 in Table 4 does not indicate the statistical significance of new firm deaths (i.e., one of the components to measure market frictions), I also apply the statistically significant results (i.e., at the 5% level) of the related coefficients from Model 9 in Table 4 and Model 1 in Table 7. I report the three versions of equilibrium vacancy due to market frictions, respectively. Based on Column 6, equilibrium vacancy due to market frictions is higher than the disposition effect in 32 of 36 MSAs and higher than the overconfidence bias in 34 MSAs. A comparison between Figures 6 and 7 shows the geographical discrepancy. Market frictions are still the leading cause of market illiquidity.

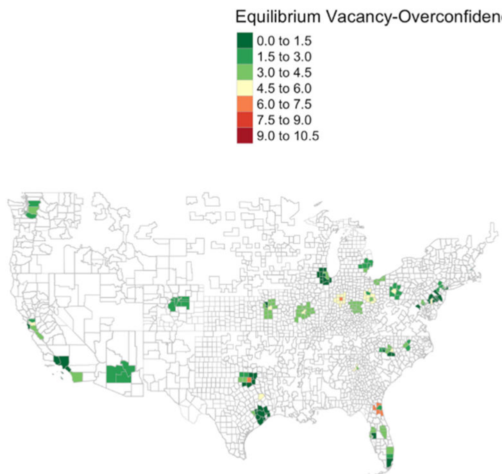
Table 6 Equilibrium Vacancy Due to Disposition Effect, Overconfidence Bias, and Market Friction at MSA Level

MSA	Disposition Effect	Overconfidence Bias	Market Friction		
			(1)	(2)	(3)
Fort Worth	6.727	5.731	6.172	6.602	7.715
Jacksonville	6.044	7.470	7.778	8.492	10.051
Orlando	5.037	3.696	4.923	5.505	6.659
West Palm Beach	5.005	6.351	6.737	7.807	9.522
Cincinnati	4.256	4.301	4.019	4.143	4.636
Fort Lauderdale	4.155	4.810	6.177	7.157	8.730
Indianapolis	4.142	4.718	4.646	4.903	5.597
Miami	3.764	3.401	3.945	4.578	5.589
Columbus	3.682	5.375	4.896	5.091	5.747
San Jose	3.498	3.232	3.905	4.394	5.241
Austin	3.407	3.796	4.366	4.686	5.555
Tampa	3.370	3.550	4.370	4.813	5.754
Charlotte	3.203	3.560	3.718	3.919	4.584
St. Louis	3.081	3.817	3.476	3.629	4.104
Oakland	2.913	2.697	2.996	3.269	3.821
Cleveland	2.688	3.685	3.018	3.054	3.459
Baltimore	2.643	2.617	2.709	2.849	3.242
Kansas City	2.642	3.399	3.121	3.311	3.774
San Francisco	2.563	1.460	1.729	1.886	2.205
Newark	2.507	2.052	2.578	2.812	3.247
San Diego	2.478	2.297	2.892	3.210	3.805
Raleigh	2.349	2.803	3.537	3.765	4.423
Denver	2.209	1.509	1.745	1.896	2.246
Phoenix	2.143	1.899	2.256	2.467	2.958
Seattle	1.753	1.533	1.861	1.992	2.319
Detroit	1.624	2.471	2.052	2.191	2.491
Pittsburgh	1.577	2.338	1.918	1.976	2.183
Dallas	1.391	0.986	1.039	1.111	1.299
Philadelphia	1.352	1.264	1.378	1.449	1.637
Houston	1.317	0.923	1.030	1.104	1.286
Atlanta	1.201	0.986	1.208	1.326	1.577
Boston	1.016	0.708	0.781	0.817	0.918
Los Angeles	0.926	0.736	0.878	0.977	1.156
Chicago	0.593	0.558	0.642	0.687	0.789
Washington, DC	0.557	0.432	0.535	0.562	0.650
New York	0.460	0.262	0.366	0.392	0.462

Notes: Since real estate markets are highly frictional which leads to misestimations of the irrational biases of investors, my identification approach can disentangle the latent effects of disposition and overconfidence bias from apparent market friction. Using Model 8 in Table 4, I estimate equilibrium vacancy driven by the disposition effect, overconfidence bias, and market friction. The estimation method is documented in the section on empirical modeling. For market friction, I also apply two other models with significant results at the 5% level to estimate its derived equilibrium vacancy. (1), (2), and (3) are estimated with the results from Models 8 and 9 in Table 4 and Model 3 in Table 7. All estimates are winsorized at the 5% level. The average values are reported in Table 6.

Figure 6 Equilibrium Vacancy due to Disposition Effect and Overconfidence Bias at MSA Level (Author Estimates)



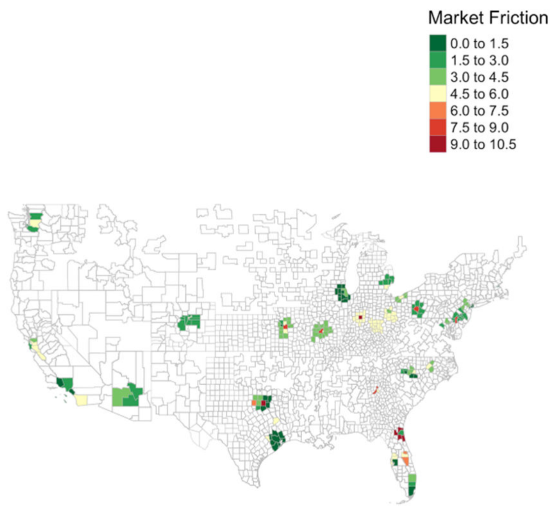


4.5 Subsample Analysis

To test the heterogeneity of the effects, I re-estimate the models separately for MSAs with below and above average levels of overconfidence and disposition. Table A2 in the Appendix summarizes the results. Comparing MSAs which have high overconfidence bias with the least overconfidence bias, the overall supply elasticity is lower in MSAs with high overconfidence bias (high bias: 0.119 vs low bias: 2.522**). High overconfidence bias has higher negative effect on supply (-0.016*** for high bias, -0.011*** for low bias). The supply elasticity driven by high overconfidence bias is lower than low overconfidence bias (0.060* for high bias, 0.303*** for low bias). Regarding the disposition effect, MSAs which has high disposition levels have lower supply elasticity (high level: -1.830* vs low level: 1.445***). There may be a contradiction of the disposition effect on supply – high disposition level which leads to a 0.007 increase in supply at the 1% level but the increment of 0.001 in supply due to low disposition level is statistically insignificant. Higher disposition effects cause a decrease in supply elasticity but the magnitude in MSAs with high disposition levels is smaller than MSAs with low disposition levels (high level: -0.069** vs low level: -0.097***).

The results also confirm that in MSAs with high disposition levels, the equilibrium vacancy is higher than in those with low disposition levels (high level: 6.718 vs low level: 3.135). MSAs with high overconfidence investors have higher equilibrium vacancy than those with low-overconfidence investors (high bias: 6.624 vs low bias: 3.466). This subgroup analysis provides further evidence that the two biases have distinct but systematic effects on real estate dynamics.

Figure 7 Market Frictional Vacancy at MSA Level with distribution based on Column 6 (Version 3) in Table 6. (Author Estimates)



4.6 Short-run Disequilibrium

The error correction term is included in the short-run rent and supply models and its coefficient can help to estimate the rate of adjustment. Based on the rent model, the coefficient of the error correction term is -0.031 at the 1% level. This implies that the rent requires approximately 32 quarters to reach equilibrium.

However, the supply model cannot find a statistically significant coefficient of the error correction term (i.e. -0.0003), therefore I cannot estimate the rate of adjustment on the supply.

5. Robustness Tests

5.1 An Alternative Measure of Overconfidence Bias

To check my measure of overconfidence bias in the main model, Model 2 in Table 3 and Model 8 in Table 4, I take an alternative measure with the direct-to-sublease vacancy ratio. The difference between the original and alternative measures is that the occupied space being re-marketed is included in the original measure. This means that the alternative measure may ignore a part of the failure. Column 1 in Table 7 presents the demand elasticity estimates and supply responsiveness by type. The estimated demand elasticity is consistent with the main result. However, the residual of the alternative demand-side cointegration equation is non-stationary; thus, the error correction model in this alternative version does not seem to be stable. On the other hand, the supply responsiveness by type is also consistent with the main result. The alternative measure of overconfidence bias is statistically significant. Therefore, this may signal that we should not ignore the failure to seek a direct tenant for re-marketing occupied space.

5.2 An Alternative Measure of Disposition Level

I also calculate an alternative measure for the tendency toward disposition by estimating the likelihood of property upgrade triggered by a higher threshold of the prime vs non-prime rental gap (i.e., 50%). I apply the same logistic models to estimate the odds ratios at the MSA level and calculate the disposition level by using the same formula. Over 75% of the odds ratios are statistically significant at the 10% level. Column 2 of Table 7 summarizes the results driven by this alternative measure. The demand elasticity is also consistent with my primary estimate. For the supply-side cointegration equation, the alternative disposition level and its supply responsiveness are very close to the main results estimated with the original measure. The magnitude of the regulatory effect on supply and responsiveness is slightly higher than in the main results. The finding suggests that an extra 10% rental gap may be affected by local regulations: for example, related to cost-driven building standards.

Column 3 reports the model results, including both the alternative measures of overconfidence bias and disposition level. The results are also consistent with the main estimates. Similar to the first alternative model, the residual of the alternative demand-side cointegration equation is non-stationary, and thus the demand-side error correction model is not stable.

Table 7 Robustness Tests

		(1)	(2)	(3)	(4)
	Alternative	**Overconfidence Bias***	**Disposition Level***	**Overconfidence* & Disposition***	**Mismatch Rate***
Demand-Side	log(Office Stock)	-0.041***	-0.042***	-0.044***	-0.040***
		(0.004)	(0.004)	(0.004)	(0.004)
	Demand Elasticity	-24.300***	-23.567***	-22.657***	-24.841***
	Time Dummies	Y	Y	Y	Y
	Adjusted R-sq	0.31	0.31	0.31	0.31
Supply-Side	log(Real Rent Index)	1.357**	1.015*	1.140**	2.085***
		(0.590)	(0.557)	(0.539)	(0.609)
	log(Real Rent Index) x Undevelopable Land Area	0.017***	0.019***	0.015**	0.015**
		(0.006)	(0.006)	(0.006)	(0.006)
	log(Real Rent Index) x Regulatory Index	0.636**	0.849***	0.842***	0.441
		(0.322)	(0.321)	(0.325)	(0.316)
	log(Real Rent Index) x Overconfidence Bias	0.009	0.110***	0.019	0.063**
		(0.013)	(0.027)	(0.013)	(0.026)
	log(Real Rent Index) x Disposition Level	-0.075***	-0.080***	-0.075***	-0.088***
		(0.013)	(0.011)	(0.012)	(0.013)
	Undevelopable Land Ares	-0.092***	-0.102***	-0.081***	-0.083***
		(0.029)	(0.029)	(0.03)	(0.028)
	Regulatory Index	-2.734*	-3.673**	-3.694**	-1.772
		(1.484)	(1.481)	(1.496)	(1.457)
	Overconfidence Bias	-0.044	-0.541***	-0.092	-0.319***
		(0.058)	(0.125)	(0.060)	(0.120)

(Continued…)

(Table 7 Continued)

		(1)	(2)	(3)	(4)
	Alternative	**Overconfidence Bias***	**Disposition Level***	**Overconfidence* & Disposition***	**Mismatch Rate***
Supply-Side	Disposition Level	0.358*** (0.059)	0.374*** (0.053)	0.353*** (0.054)	0.419*** (0.058)
	New Firm Birth	0.023** (0.010)	0.042*** (0.010)	0.032*** (0.010)	0.025** (0.010)
	New Firm Death	0.073*** (0.027)	-0.004 (0.028)	0.069** (0.028)	0.032 (0.029)
	Time Dummies	Y	Y	Y	Y
	Adjusted R-sq	0.53	0.53	0.52	0.55

Notes: Four robustness tests with alternative measures of overconfidence bias, disposition effect, and mismatch rate are reported. The alternative measure of overconfidence bias is the direct-to-sublet vacancy ratio. Compared with the original measure, space that is still occupied by existing tenants but open to the market is excluded. In other words, the alternative measure rules out the mismanagement which causes a gap in contractual terms. For the disposition effect, I estimate the likelihood of property upgrade where the prime vs non-prime net asking rental gap is larger than 50% and calculate an alternative measure for the disposition level by using the same approach. The alternative mismatch rate is determined with the ratio of economic mismatch (i.e. space which is still occupied but open to the market) to vacant space. I apply the same Engle-Granger demand-side and supply-side cointegration equations separately on the alternative variables to compare the main results in Table 3 and 4 (version: Wharton Regulatory Index 2008). The residual of the demand-side cointegration equation in Models 1 and 3 is non-stationary. ***, ** and * represent significant results at the 1%, 5%, and 10% levels, respectively. The standard error is reported in parentheses.

5.3 An Alternative Measure of Economic Mismatch

I alternatively calculate the economic mismatch rate as the ratio of occupied available space to vacant space. The results also show a comparison between re-marketed occupied space and the vacant condition. Column 4 reports the results of the alternative model. The results are also consistent with the main estimates. However, the regulatory effect on supply and its supply responsiveness is statistically insignificant. This finding might imply that there are specific regulations related to vacant offices. Therefore, significant results that pertain to regulations cannot be found.

In summary, all of the robustness tests confirm that my results are valid and reliable.

6. Conclusion

This paper proposes an approach for observing operating decisions to identify the effects of overconfidence bias and disposition in real estate markets with frictions. I employ a sample of 38 MSA-level office markets, which cover 61% of the office workforce from 2005Q1 to 2019Q4, to quantify these two kinds of irrational biases of CRE investors, and their impacts on real estate supply responsiveness and market illiquidity. In this study, I argue that the disposition effect is relatively "self-perceived", compared to overconfidence biases.

First, I explain how these two kinds of irrational biases affect real estate supply responsiveness and equilibrium vacancy, in terms of operating decisions (i.e., overconfident investors fail to seek direct tenants, and investors with a disposition tendency hesitate to upgrade significantly depreciated properties (assets with reducing value due to wear and tear)).

Secondly, I propose an innovative approach to measure overconfidence bias and the disposition effect and disentangle their effects from market friction. As the overconfident characteristics are latent, I confirm overconfidence bias only when certain investors face failure but rational investors do not. In the extant literature, the measure of overconfidence bias based on aiming for a higher than average return may entail problems of misspecification or inappropriate caliber, due to the difficulties of effectively identifying this kind of bias. I observe operating decisions in which investors choose to direct-lease but forgo secure income flow from giving permission to sub-lease, in order to define confident or overconfident investors. As overconfidence is only expressed in terms of failed investors, I examine the ratio of direct-to-sublease availability (vacancy). The identification approach helps to measure the relative strength of the bias at the MSA level. Moreover, another observation related to decisions to upgrade the real estate quality is used to estimate the power of the disposition effect.

Thus, this study is the first attempt to accurately measure two types of irrationalities at the MSA level by using a novel dataset.

Thirdly, tenants generally tend to be rational, as the demand for offices is very elastic. Although regulations have the most significant impact on overall rental supply, and overconfidence bias ranks second, supply responsiveness is the slowest resultant of geographical barriers. Even investors with a tendency toward disposition would reduce rentable supply when the market rent increases. I also confirm that each disposition effect at the MSA level has the greatest impact on supply responsiveness. This finding suggests a policy recommendation: to enhance supply responsiveness by providing technical support for property upgrades in areas with strong disposition effects. Such support may help irrational investors to make their decisions more quickly.

Moreover, I discuss how the disposition effect and overconfidence bias affect real estate market illiquidity, and compare their impact with that of market friction. I identify market friction in rental markets with the net business survival of new firms, and propose equilibrium vacancy to measure market illiquidity. Market friction is the leading cause of market illiquidity, but irrational factors are also significant. In most MSAs, equilibrium vacancy due to the disposition effect is higher than that caused by overconfidence bias; this implies that the disposition effect occurs more frequently, which is consistent with my argument. In addition, the highly positive correlation between supply responsiveness of overconfident investors and related equilibrium vacancy implies that inaccurate market forecasting of overconfident investors leads to over-reaction, and their wrong decisions increase the illiquidity of the market.

Relative to Marcato and Tong (2023), who focus on search frictions in the office markets, this paper contributes by quantifying the role of behavioral biases in shaping supply responsiveness and market liquidity. By developing novel MSA-level measures of overconfidence and disposition based on operating decisions, the study provides the first empirical evidence of latent irrationality in real estate markets beyond investment transactions. This complements the friction-based literature and highlights the importance of behavioral heterogeneity in explaining illiquidity in CRE.

A novel insight from this study is the distinction between cyclical and structural behavioral biases. Overconfidence operates as a time-varying phenomenon, rising and falling with market cycles, whereas the disposition effect is a structural tendency, persistent across cycles within each MSA. This distinction matters for policy and market analyses; cyclical biases may require short-run monitoring and market transparency initiatives, while structural disposition effects may call for longer-term interventions such as incentives for property upgrades.

In a future study, I intend to apply the estimates from this study to examine how overconfidence bias and disposition effects affect mortgage risks, given that most real estate investments are leveraged. Both studies contribute to the literature by offering empirical evidence on irrational biases in frictional markets.

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Appendix

Table A1 Tests of Exogeneity of Overconfidence Bias and Disposition Effect

	Instrumental Variable for Overconfidence Bias	Instrumental Variable for Disposition Effect	Instrumental variables for Overconfidence Bias and Disposition Effect
Hausman Chi Square	2.26	3.34	7.91

Notes: Hausman tests are conducted to test exogeneity of overconfidence bias and disposition effect. The ordinary least square model for the cointegration equation (i.e., Model 5 in Table 4) is treated as the benchmark. Lagged submarket vacancy rate differential and the percentage of Classes B/C office stocks are used as instrumental variables for overconfidence bias and disposition effect, respectively. The regression models with instrumental variables are set up to conduct the Hausman test through a comparison with the benchmark. All the chi squares are statistically insignificant at the 10% level. This indicates that the test results fail to reject exogeneity. It is concluded that overconfidence bias and disposition effect are exogenous.

Table A2 Sub-Sample Analysis

	High Overconfidence Bias	Low Overconfidence Bias	High Disposition Level	Low Disposition Level
log(Real Rent Index)	2.486*** (0.902)	0.831 (1.425)	-0.434 (1.574)	3.258*** (0.790)
log(Real Rent Index) x Undevelopable Land Area	0.037*** (0.010)	0.023** (0.010)	0.004 (0.012)	0.064*** (0.006)
log(Real Rent Index) x Regulatory Index	0.999** (0.485)	1.238** (0.483)	0.063 (0.489)	4.000*** (0.406)
log(Real Rent Index) x Overconfidence Bias	0.060* (0.034)	0.303*** (0.070)	0.133*** (0.037)	-0.106*** (0.038)
log(Real Rent Index) x Disposition Level	-0.127*** (0.019)	-0.031 (0.020)	-0.069** (0.029)	-0.097*** (0.029)
Undevelopable Land Area	-0.175*** (0.046)	-0.122*** (0.044)	-0.036 (0.054)	-0.283*** (0.028)
Regulatory Index	-4.182* (2.214)	-5.496** (2.240)	-0.079 (2.250)	-18.18*** (1.874)
Overconfidence Bias	-0.337** (0.156)	-1.454*** (0.326)	-0.656*** (0.170)	0.466*** (0.177)
Disposition Level	0.589*** (0.088)	0.155* (0.091)	0.346*** (0.135)	0.452*** (0.129)
New Firm Birth	0.029** (0.012)	0.039** (0.019)	0.077*** (0.013)	0.002 (0.012)
New Firm Death	-0.159*** (0.042)	0.005 (0.044)	0.019 (0.045)	-0.427*** (0.038)
Wharton Regulatory Index				
2008	Y	Y	Y	Y
Time Dummies	Y	Y	Y	Y
Adjusted R-sq	0.63	0.51	0.63	0.59
Observations	940	1025	994	971

Notes: To test the heterogeneity of irrational biases, I re-estimate the models (i.e., Model 8 in Table 4) separately for MSAs with above and below-average levels of overconfidence bias and disposition effect. This table exhibits the results of four sub-groups: (1) high overconfidence bias, (2) low overconfidence bias, (3) high disposition level, and (4) low disposition level. The dependent variable is log(office stock). Log(mismatch rate) and log(search effort level) which are I(0) are included. Other exogenous variables are included: real operating expense growth, change in capitalization-T yield gap, port city dummy, and travel time to work dummy. Their results are not reported. The residual of each cointegration equation is stationary at the 1% significance level. ***, ** and * represent significant results at the 1%, 5%, and 10% levels, respectively. The standard error is reported in parentheses.