Supply Elasticity, Constraints, and Search Equilibrium in Commercial Real Estate Markets*

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Abstract

In the current revolutionary shift of nature of office space demand, we focus on the offer response to demand changes by presenting a new conceptual model for the estimation of office supply elasticity in commercial real estate markets. We transfer concepts from labour economics to define frictional and structural vacancy and develop a theoretical framework where both physical and economic mismatch lead to either permanent or temporary levels of vacant space within a fundamental real estate cycle model. Empirically, we identify economic mismatch by observing landlords who re-let occupied space. Estimating an error correction model with 4 simultaneous equations, we determine the long-run equilibrium and matching process from short run disequilibrium to estimate elasticity and structural vacancy rate in 42 Metropolitan Statistical Areas (MSAs) covering almost 50% of the entire US population. We find that all MSAs are supply inelastic and our results are consistent with previous studies in housing markets. We also prove that the search and matching process is significant and improves the ability to explain our results. Finally, a positive correlation between estimated supply elasticity and structural vacancy implies that the low controlling power of landlords reduces the flexibility in adjusting equilibrium vacancies to respond to market shocks. Thus supply elasticity is likely to be explained entirely by geographical and regulatory constraints.

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Keywords: Supply Elasticity and Constraints, Structural Vacancy, Commercial Real Estate, Search Equilibrium

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1 Introduction

The price responsiveness to property supply always draws great interest among policy makers, particularly in the literature investigating house price bubbles. Over the last decade we have witnessed a revolutionary shift in the nature of office space demand from individual offices to collaborative space. On one hand all major corporations (e.g. Facebook, Google, Ernst and Young, PricewaterhouseCoopers) have been advocating for open and shared workspace and adopted work-from-home policies. On the other hand, smaller companies (especially ventures and sole traders) have been using shared office facilities to efficiently maximize networking opportunities offered by new providers of workspace. Moreover, less demand in office space is foreseen when more on-site tasks are assigned and more tedious work is superseded by automation. Facing all these changes, the ability of supply to adjust to new requirements and hence the presence of supply constraints in office sectors can be used to predict the impact of a negative demand shock on property prices.

Supply constraints are generally classified into two main categories: regulatory and physical. Regulatory constraints are measured by the tightness of a development approval process, which is usually identified through surveys (Gyourko et al 2008 [17], Saks 2008 [31]). Saiz 2010([30]) introduced the empirical strategy where land unavailability is measured to solve the endogenous problem, identifying both regulatory and physical constraints of housing supply, and quantifying their tightness. Overall constraints are quantified by supply elasticity which is mostly estimated using an urban growth-based econometric model.

We may argue that supply elasticity for offices should be positively correlated with the one in housing markets because the tightness of planning regulation and geographical barriers should not differ within the same area. However, missing empirical evidence for non-residential markets, different dynamics of market competition between suppliers and divergent incentives to control the restrictiveness of supply constraints between different property markets motivate us to estimate office supply elasticity by metropolitan statistical area (hereafter MSA).

In fact, the existence of more strategic investors in the office sector than in residential markets leads to the availability of office space supply which tends to be "manipulated". In fact, supply in equilibrium could be determined by their approach to control the flow of available office space as their strategy is rooted in the search and matching theory, applied first in housing markets, e.g. Wheaton (1990[37]). Since lease contracts are long-term and have fixed rents, landlords strategically keep a predefined amount of vacant space to seek for high-profile tenants who will afford higher rents and allow them to maximise their profit. This amount of space may also vary over boom and bust cycles. In our paper we define this situation as *economic mismatch* where a bid-ask rental gap exist until landlord and tenant's requirements match and the vacant space is occupied. This mismatch situation may also be present in a long run equilibrium increasing the *natural vacancy rate*. Simultaneously, the vacant space in non-prime (i.e. class B or C) office buildings is due to its old-fashioned and worn-out physical design that requires a refurbishment to prime quality before their use can be guaranteed. We define this phenomenon as *physical mismatch* and we argue that it can also increase the long-run natural vacancy rate. Unlike in housing markets where households act as both buyers and sellers and the searching process mainly affects the short-run disequilibrium, office landlords (i.e. sellers of a space rental service) with higher controlling power are capable to alter the long-run equilibrium of supply. As a consequence, we believe that the equilibrium vacancy is highly important because it may distort the responsiveness of rents to office supply.

At this point the analogy of real estate and labour markets (where a well established search and matching model can be applied) helps us to transfer the concept of unemployment to unoccupied space, distinguishing three types of vacancy: cyclical, structural and frictional. This set up also sheds light upon the three components driving long-run vacancy: mismatch rate, search effort level (for structural) and demand of refurbishment (for frictional). We find that a search equilibrium does exist and we show that equilibrium vacancy should be determined at the time of the search equilibrium.

We initially build a conceptual framework to link supply elasticity and long run vacancy. We then suggest an empirical strategy to identify economic mismatch - i.e. space in use which is available for re-let to new tenants instead of existing tenants - to quantify the search effort - i.e. relative size of available letting space listed - and to determine a simultaneous equilibrium in the market and the search and matching process using an error correction model.

Our empirical findings support our argument that search equilibrium is essential to estimate office supply elasticity, which is found to be positively correlated with structural vacancy. As low structural vacancy implies less control by landlords, we argue that the price responsiveness to supply changes is almost completely explained by regulatory and geographical issues when office sectors are supply inelastic.

The paper is organized as follows. The next section provides a literature review related to supply constraints, vacancy and search equilibrium. Section 3 presents our conceptual model. In section 4, we explain our empirical strategy including data description and error correction model framework. Sections 5 and 6 include main results, robustness tests and a discussion about supply elasticity rankings by MSA.

Finally, we draw our conclusion with limitations and further research directions in the last section.

2 Literature Review

Property supply is a crucial factor in property market dynamics along with demand shocks and we find a growing number of studies on supply constraints and their policy implication, especially in housing markets. In contrast, supply constraints are under-explored in commercial property markets. As the variation of supply elasticity by city/municipality is found significant but a data shortage exists globally, the majority of studies focuses on US housing markets. Three seminal studies estimate supply elasticity for more than 40 MSAs (Green, Malpezzi and Mayo 2005[15], Saiz 2010[30], Wheaton, Chervachidze and Nechayev 2014[38]). Green, Malpezzi and Mayo argue that the variation of supply elasticity among 44 MSAs is explained by the difference in local regulation. Saiz suggests an empirical strategy to prove Green et al's argument, to solve the endogeneity issue and to identify physical and regulatory constraints for 95 MSAs by quantifying land unavailability through Geographical Information System (GIS) and referring to the Wharton residential land regulatory index. Wheaton et al provide a unique approach merging the stock-flow framework and urban growth theory to disentangle the short run disequilibrium from the long term trend of housing prices and to estimate both long-run and short-run supply elasticity for 68 MSAs.

Large scale surveys about planning approval could be used to measure the stringency of regulatory supply constraints. However, intensive resources and well designed questionnaires are required to mitigate the "selection bias" in information disclosure by interviewees. So far, the Wharton Residential Land Use Index compiled by Gyourko et al (2008 [17]) and the Saks's composite index (2008[31]) are frequently cited among these attempts. The former consists of 11 sub-indices regarding political pressure, ease of zoning approval, supply and density restrictions for 293 MSAs. Data was collected through the largest survey where planning directors of around 2600 municipalities were interviewed in 2000's. Because of high response rates, it represents the most reliable measurement of regulatory constraints to date. The latter, instead, was constructed by taking the average of six independent surveys related to processing time of zoning approval, severity of population growth controls, protection of historic sites and environmental regulation conducted for 83 MSAs between 1975 and 1990. Although Saks covered less MSAs, the index is considered robust and often cited in the literature.

Table 1 exhibits the Spearman rank correlation matrix of the five main estimations of supply elasticity or regulation indices in the US market. Since some indices report elasticities and some others refer to constraints, we make the comparison easier by reporting absolute values. In general, findings for housing supply constraints are consistent. Overall, correlation coefficients of Saiz's supply elasticity with other indices (except for Wheaton's long run supply elasticity) are the highest, followed by the Wharton index. This evidence may be attributed to similar methodologies adopted by Saiz, Gyourko et al and Saks et al. Since Green and Wheaton applied different methods, relatively lower correlations are found. In this table we also present the correlation coefficients of our estimated office supply elasticity with these studies (last two rows and columns) and, as expected, we find correlated supply constraints for commercial and residential property markets (further discussion will be included in Section 6).

[Insert Table 1 Here]

Compared to housing markets, regulatory constraints in commercial real estate curtail fiscal revenues to a greater extent, but they reduce negative externalities such as congestion and pollution. As a result, the restrictiveness of supply constraints in commercial property markets is even more driven by local circumstances when local governments attempt to reconcile their fiscal need with concerns for the living environment (Fischel 1973 [10]). Since commercial data is hard to access, rare empirical studies on supply elasticity are found in non-residential markets. Benjamin et al (1998)[2] are an exception and study retail space supply elasticity for 34 MSAs and distinguish short- and long-run by adopting a stock flow model. Since an endogenous cycle driven by longer production lags and lease terms in commercial markets adds complexity to the structure of housing ones, the short run disequilibrium shall not be ignored as a biased estimation of supply constraints may be obtained. Moreover, a stock flow model is the most appropriate approach to disentangle the short-run disequilibrium from the long-run state.

So far, causal relationship between supply constraints and vacancy is not considered to estimate supply elasticity. Only two aforementioned studies - Benjamin et al (1998) and Wheaton et al (2014) - implicitly involve imbalances between supply and demand by using a stock-flow model where vacancy is captured in the estimation of supply elasticity. Cheshire et al (2016)[4] fill this gap and show that tightening regulatory constraints on housing markets in the UK significantly push vacancy rates up because inflexible planning hinders the matching process - demand for housing characteristics is satisfied. Furthermore, they point out that in office markets an increase in price volatility motivates landlords keeping properties empty since the value of

real option (i.e. an option to wait) increases. Fluctuations in vacancy rates driven by mismatch hinge on supply constraints and may function as an alternative check on the plausibility of supply elasticity estimates. Hence, importantly, equilibrium vacancy has to be considered.
When markets clear, an equilibrium is reached but the vacancy rate is not necessarily equal to zero. Academic researchers have started to investigate equilibrium vacancy rates since late 1980s. Most scholars - Rosen and Smith (1983)[29], Gabriel et al (1988[11] and 2001[12]), Shilling et al (1987[33]), Jud et al (1990[20]), Englund et al (2008[8]), Hendershott et al (2013[19]) - refer to it as natural vacancy, or the rate of unoccupied space where rents remain unchanged. Others - e.g. Wheaton and Torto (1988[39]), Sivitanides (1997[34]) - refer to it as structural vacancy, but their definition and estimation approach - rental adjustment originally developed by Eubank and Sirmans (1979)[9]) - do not differ from the former. Moreover, frictional vacancy is discussed similarly to structural vacancy (Wheaton and Torto (1988[39]). However, if we fully transfer the concept of unemployment in labour markets to the one of vacancy in real estate markets, we may be able to better understand the role of natural vacancy, its components and the causes of disequilibrium and therefore to develop a conceptual framework of real estate cycles in conjunction with supply constraints.
Search frictions inevitably derail competitive price formation in property markets and cause vacancy. This requires studies with the assumption of imperfect property markets, where clearance is not instantaneous and without cost. The search and matching theory is developed by Diamond (1971[6]) to explain unemployment in labour markets. Diamond (1971[6])'s paradox suggests that even small search costs drive equilibrium from competitive to monopoly price. Further theoretical work by Diamond (1982[7]) features multiple steady-state rational expectations equilibria implying that the economy with trade frictions - (Salop 1979[32]) - does not have a unique natural rate of unemployment due to search externalities generating inefficient outcomes at the macro level - i.e. time-varying features of natural unemployment exist. Since the concept of natural vacancy in property markets is similar to the one of natural unemployment in labour markets, we can expect time-varying characteristics for natural vacancy as well. Diamond's model to find equilibrium is rooted in the lifetime utility earned by an individual who switches from employment to unemployment. This has become the foundation of equilibrium models featuring search and matching and further developments are presented by Mortensen and Pissarides (1985[26], 1994[24] and 1999[25]) who analyse how aggregate shocks lead to cyclical fluctuations in unemployment, job vacancy and employment flow simultaneously. An aggregate matching function is set up to describe the search process

between workers and firms. Whether a search process is sequential (i.e.once an action is taken in one period and consequentially several new actions become available in next period) or non-sequential depending on the searching methods, a search equilibrium does exist (Keller and Oldale 2003[21], Van Ommeren and Russo 2014[35]) and it is reached when unemployment is maintained at equilibrium state, i.e. natural rate of unemployment, whose three components can be identified separately:

- **structural unemployment** is due to the presence of workforce demand not matching the offer because of economic reasons
- **frictional unemployment** is due to the difficulty of matching workforce skills with requirements from demand;
- **cyclical unemployment** is related to short term fluctuations due to temporary phenomena (e.g. workforce mobility).

On one hand, the existing literature in real estate markets studies the creation of temporary inventories by landlords to maximize net rental receipts during periods of strong demand - Rosen et al (1983), Shilling et al (1987), Gabriel et al (1988), Wheaton et al (1988). In fact, landlords sometimes hold vacant space deliberately until they reach *ideal tenants* who can afford higher rents, i.e. with a *rental floor* above the equilibrium level (economic mismatch, even with a physical match). If we also consider the search process, deliberately holding vacant space may lead to an extension of the searching time. On the other hand, we could also observe vacant space because the physical characteristics of a building become obsolete for the new demand and hence a refurbishment becomes necessary to reach occupation. So far in the literature, these two features are not jointly studied and we believe it is insightful to embed them both in a model to investigate how this behaviour determines equilibrium vacancy and market disequilibrium. In order to do so, we firstly identify three types of vacancy mirroring the labour literature:

- **structural vacancy** derives from landlords holding empty buildings to wait for higher future rents (economic mismatch)
- **frictional vacancy** relates to the space on offer whose physical characteristics cannot be matched with tenants‘ requirements and hence it is not absorbed until being refurbished (physical mismatch)
- **cyclical vacancy** refers to the excess property supply due to short term fluctuation in economic or business conditions (economic mismatch)

Importantly, the simultaneous effect of cyclical and structural/frictional factors on unemployment represents an obstacle to the empirical identification of each unemployment type (Rissman 1986[27]). However, while cyclical factors lead to short-run unoccupied space, structural and frictional factors tend to affect the long-run equilibrium state. Hence, the estimation of an error correction model offers a suitable approach by separating the short-run impact from the long-run trend. In our model, short-term fluctuations will result from search disequilibrium and economic shocks. Wheaton (1990[37]) extends the search and matching model from labour markets to housing markets, and he assumes structural vacancy being equivalent to natural vacancy and computed as (1 - number of households/housing units) upon the condition that expected house prices equal marginal supply costs. Matching statuses vary by changes in households which turn into new demand for larger or smaller houses and the matching speed relies on the search effort required. To smooth the matching process, vacant houses are necessary in the long-run and structural vacancy can be explained by market activities. In our conceptual model, we follow Wheaton(1990[37])'s illustration of structural vacancy and jointly determine this type of vacancy with a matching process. Building our conceptual model, we also empirically demonstrate the importance of search and matching to estimate supply elasticity in office markets.

3 Conceptual Framework

We set up the conceptual model to determine the relationship between natural vacancy and supply elasticity in commercial real estate rental markets following the previous work of Wheaton (1990[37]) in housing markets. We classify *mismatch* between tenants and landlords into two categories: economic and physical. *Economic mismatch* is defined as the point at which desired rent levels (r^D) of a landlord cannot be satisfied. In other words, all bid rents offered by tenants (r^B) are lower than the landlord's asking rent. For physical matching, instead, we distinguish property space (S) as defined by N heterogeneous characteristics, i.e. building facilities such as ventilators, lifts, car parks, panoramic views, size, etc.. If the combination of unique characteristics differs, we count it as another bundle and thus i is the element of the set (I = 1, $\cdots$, N ; N: total number of bundles of heterogeneous characteristics). Tenants' required property characteristics (j) can be divided into two groups: (1) matched with space characteristics provided, and (2) partially unmatched characteristics. Some provided space characteristics may be also redundant and no tenant requires them. J denotes the set of bundles of tenants' required characteristics, and its major part is the overlapping subset with I. *Physical mismatch* is identified by

the second group of J and redundant space characteristics offer. Suppose some i match with j belonging to the first group of J, we denote i as i_m indicating with subscript m that characteristics are matched. Instead, bundles of characteristics i not matching j are defined as i_n, where subscript n stands for non-matched (i.e. mismatched) characteristics. If we consider the time-varying feature of property space in the long-run, the supply of space can be categorized as follow: $S_{i_m,l,t}$ and $S_{i_n,l,t}$, where t represents time.
Combining physical and economic matching, space supply is divided into four main groups:

- Both economic and physical match: $S_{i_m|r_t^B \geq r_t^D,l,t}$
- Economic mismatch and physical match: $S_{i_m|r_t^B < r_t^D,l,t}$
- Economic match and physical mismatch: $S_{i_n|r_t^B \geq r_t^D,l,t}$
- Both economic and physical mismatch: $S_{i_n|r_t^B < r_t^D,l,t}$

3.1 Vacancy Type

Vacancy (classified as mismatched space) depends on both economic and physical matching. If both economic and physical characteristics are matched, the space is occupied by tenants. At time 0 (i.e. when a rental contract is signed), all deals are made in the condition that both economic and physical requirements are satisfied. Long term leases lead to changes in mismatch status of occupied space because of immediate rent adjustments by landlords and/or tenants moving to suitable office space based on their latest requirements. This short- vs long-run dynamic implies that the mismatch status of occupied space may switch among the four aforementioned groups, with a minor role played by the last group. On the other hand, new tenants may introduce new requirements of space characteristics and subsequently bid and/or asking rents may change as a consequence. Clearly, the status of vacant space may vary over time among the last three types (excl. joint economic and physical match). We further classify space supply according to its tenancy (occupied vs vacant) and the mismatch status (matched vs non-matched and economic vs physical) in the following equation:

$$
\begin{aligned}
S_{i,l,t} = {} & S_{i_m|r_t^B \geq r_t^D,l,t}(occupied) + S_{i_m|r_t^B < r_t^D,l,t}(occupied) + \\
& S_{i_n|r_t^B \geq r_t^D,l,t}(occupied) + S_{i_n|r_t^B < r_t^D,l,t}(occupied) + \\
& S_{i_m|r_t^B < r_t^D,l,t}(vacant) + S_{i_n|r_t^B \geq r_t^D,l,t}(vacant) + S_{i_n|r_t^B < r_t^D,l,t}(vacant)
\end{aligned}
\tag{1}
$$

When the search and matching process is completed, a short-run stable equilibrium is reached, where physically mis-matched space would not be occupied any longer. Therefore, $S_{i_n|r_t^B \geq r_t^D,l,t}$(occupied) and $S_{i_n|r_t^B < r_t^D,l,t}$ (occupied) equal zero. Moreover, we can identify the condition for which both economic and physical mismatch exist. Equation 1, thus, can be simplified to equation 2 to describe the short-run equilibrium.

$$
\begin{aligned}
S_{i,l,t} = S_{i_m|r_t^B \geq r_t^D,l,t}(occupied) + S_{i_m|r_t^B < r_t^D,l,t}(occupied) + \\
S_{i_m|r_t^B < r_t^D,l,t}(vacant) + S_{i_n,l,t}(vacant)
\end{aligned}
\tag{2}
$$

Following a three way decomposition of the vacancy rate taken from the labour literature, we then identify the three types of vacancies as follows:

Structural vacancy: Landlords deliberately hold vacant space (maybe unlisted) until reaching out to their *ideal tenants* who can afford rents exceeding an equilibrium level, i.e. a *rent floor* is set above the equilibrium level. Assuming that the space characteristics match tenants' requirements but bid rents are lower than asking rents, structural vacancy ($V_{l,t}^s$) is a percentage rate of $S_{i_m|r_t^B < r_t^D,l,t}(vacant)/S_{i,l,t}$ that we classify as *economically mismatched and physically matched*.

Frictional vacancy: The process of matching physical characteristics of building may lead to the formation of vacancy. A certain amount of space may not match tenants' requirements and hence it may not be occupied until it is renovated. We qualify this type of vacant space as *physically mismatched* and according to equation 2, frictional vacancy ($V_{l,t}^f$) is obtained as $S_{i_n,l,t}(vacant)/S_{i,l,t}$.

Cyclical vacancy: Excess property supply results from short term fluctuations in the general economy or the specific business sector which requires office space. However, responses of tenants and landlords to short term shocks are delayed because of fixed term leases and construction lags. This type of vacant space ($V_{l,t}^c$) is supposed to match with tenant's requirements and we classify it as "economically mismatched and physically matched".

To summarize, a natural vacancy rate ($V_{l,t}^n$) exists in the long-run and the sum of structural and frictional (non-cyclical) vacancy represents its measure. Particularly, structural vacancy represents the non-cyclical component of $S_{i_m|r_t^B < r_t^D,l,t}(vacant)/S_{i,l,t}$.

3.2 Short Run and Long Run Supply Curve

Following Helsley and Strange (2008) [18], we construct the increasing and convex construction function with respect to building height and the concave profit function of a developer. To benefit from economies of scales, a developer decides how many floors should be built to maximize the profit. This convex construction function implies a convex kinked long-run supply curve.

$$\pi(h_{l,t}) = r_{l,t}h_{l,t} - c(h_{l,t}) \tag{3}$$

π: developer's profit
$h_{l,t}$: building height for a developed property which is located in city l at time t
$r_{l,t}$: rent per floor for a property in city l at time t
c: construction function.

When $r_{l,t} = c'(h_{l,t})$, the profit is maximized. New supply is assumed to match tenants' needs as developers thoroughly study tenants' demand and their preferences of property characteristics before building. In addition, we assume that developers also base their investment decision on expected rental growth, with demand shocks in property markets leading to changes in expectations about future rents. The short run supply is extremely inelastic as weak responsiveness to rental change is exhibited due to the existence of construction lags.

3.3 Short Run and Long Run Equilibrium Rent

The demand function ($D_{l,t}$) of commercial properties is driven by factors linked to industry-related revenues and expectations about the future business environment. The income growth for residents may reflect the prosperity of the business environment since more bonuses would be shared with employees in a robust economy. A demand shock is normally triggered by a change in the business environment such as a shock in employment in business sectors renting office space for operations. At the same time, we assume that corporations can execute an immediate plan to adjust the workforce after anticipating the future business outlook. In other words, current employment ($EM_{l,t}$) in city I at time t indicates the expectation about the future business environment, which drives demand for space. Along with aggregate income for residents ($RI_{l,t}$) and rents ($r_{l,t}$), Equation 4 describes the long-run demand.

$$D_{l,t} = f(EM_{l,t}, RI_{l,t}, r_{l,t}) \tag{4}$$

The figure below shows the effect of a positive shock to the aggregate demand (from

$AD1$ to $AD2$) due to a sudden increase of employment due to a company relocation to the city. Rents increase and as a consequence, the amount of supply slightly increases. However, the growth is curtailed by an inelastic short-run supply.

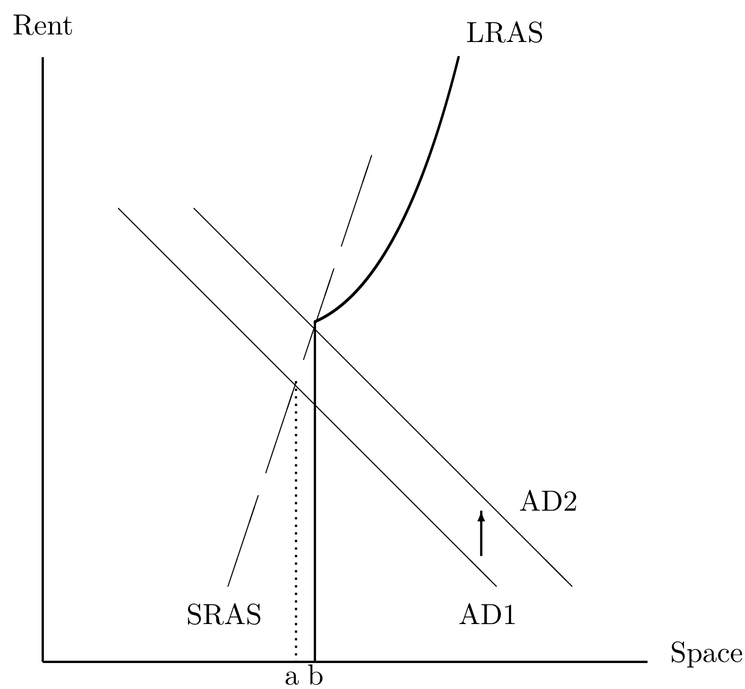

Figure 1: Long- and Short-Run Aggregate Demand and Supply Curve of Property Space

At the point of long-run equilibrium, the demand ($D_{l,t}$) for office space should exactly equal the amount of supply ($S_{l,t}$) after some adjustments. However, a small component of supply remains unoccupied because of market frictions (search and matching is costly, i.e. frictional vacancy: $V^f_{l,t}$) and the landlords' strategy of holding vacant space for future gains (i.e. structural vacancy: $V^s_{l,t}$). Hence, we expect that in equilibrium demand equals supply only after deducting vacant space due to frictional and structural vacancy as described in the following equation.

$$D_{l,t} = (1 - V^f_{l,t})(1 - V^s_{l,t})S_{l,t} \tag{5}$$

In the short-run, changes in demand are not completely met by changes in supply. The *satisfaction*, quantified by space absorption, hinges on matching rates ($\omega_{l,t}$) of tenants in market l. As suggested in Cheshire et al (2016)[4], a matching rate is determined by the level of search effort required ($\epsilon_{l,t}$) and the ratio of vacant property to mismatched tenants ($\theta_{l,t} = S_{l,t}(\text{vacant}) \;/\; S_{i_m|r^B_t<r^D_t,l,t}(\text{occupied})$) through a

constant return to scale Cobb-Douglas matching function:

$$\omega_{l,t} = \alpha * \epsilon_{l,t}^{\beta} * \theta_{l,t}^{(1-\beta)} \tag{6}$$

where α is a constant and β represents the weighting. Therefore, space absorption can be described as Equation 7. If demand was fully bet, the distance *"ab"* in the above diagram would indicate the net absorption in the short-run.

$$AB_{l,t} = \Delta D_{l,t} * \omega_{l,t} \tag{7}$$

Simultaneously, a construction lag hinders immediate supply responses and, as a result, changes in supply are not fully realized. In order to reflect an effect of construction lag in our empirical investigation, a lagged change in supply is singled out for determining a change in vacancy and z in Equation 8 represents the number of construction lags.

$$\Delta V_{l,t} = \Delta S_{l,t-z} - \Delta D_{l,t} * \omega_{l,t} \tag{8}$$

Assuming that one unit of demand shock in the market stimulates one percent increase in rents, Equation 8 suggests that a change in vacancy can be estimated by subtracting the matching rate from the responsiveness of supply. A matching rate model is used to identify structural vacancy and, assuming negligible frictional vacancy rates, a change in vacancy could be decomposed into supply elasticity and structural vacancy.

4 Empirical Strategy

4.1 Econometric Model

The systems of long- and short-run simultaneous equations are constructed based on the above conceptual framework to find empirical evidence for our arguments:

- the cyclicality of a commercial real estate market is determined by a search and matching process which identifies structural vacancy;
- the search and matching process is necessary to estimate supply elasticity consistently.

Our empirical model captures the mismatch between tenants and landlords, and the search effort required to find the search equilibrium. First, we derive the equation of long-run real rent from the demand function (Equation 4) and subsequently we add the mismatch variable, which proxies for the need of searching. Second, we assume that landlords are capable of controlling the matching process. Therefore, the long-run supply equation contains both a mismatch rate and search effort level, which are determined by the quantity of information about available properties. Moreover, operating expenses charged by property management firms and the difference between capitalization and mortgage rates are considered as cost shifters. Equation 10 describes the long-run supply relationship.

Third, because of a concern about endogeneity in the matching process, we introduce simultaneous equations for search effort level and mismatch rate. The equation of search effort level is constructed with real aggregate personal income which proxies for business outlook (an exogenous variable), rents and supply that are endogenous factors in the search process. A change in city size which is identified by a change in population alters the mismatch rate because new tenants may increase demand moving in from other cities. Shifts in business outlook are also considered because the tenants' plan for expansion and landlords' strategy to seek "targeted" tenants may be altered. The equation of mismatch rate, therefore, contains population and aggregate personal income as proxies for business outlook, along with property supply.

As a whole, four long-run equations are built in the simultaneous system, where variables are transformed in natural logarithms (excl. mismatch rate, search effort level and cap minus mortgage rates). $\mu_{l,t}$ represents the residual of each long-run equation and the lagged term $\mu_{l,t-1}$ is the error correction term used in the short run equations to compute speed of adjustment to reach a long-run equilibrium. The simultaneous system is solved using a three-stage least squares estimation.

Lag Selection

As the business outlook is normally projected based on actual performance over the last full year and corporations adjust their headcount over the following two quarters, an expansion of office space should be decided following a change in their work plan. Therefore, we choose a four-quarter lagged aggregate income, two-quarter lagged employment index and one-quarter lagged office stock in our estimation. Furthermore, landlords may adjust asking prices based on recent evidence of economic mismatch and hence a rental adjustment may be realized upon a deal being done. As a result, a one-quarter lagged economic mismatch rate is selected.

As far as the supply equation is concerned, we rely on the findings about time-to-plan and time-to-build for non-residential buildings by Millar et al (2012[22]) and Montgomery (1995[23]) and use a time lag of 11 or 12 quarters (i.e. sum of these two time lags) for real rents, real construction costs and real operating

expenses[1]. Although costs for funding should be considered in parallel with rents for appraisal purposes, we also need to consider the timing needed to release almost or just completed space based on foreseeable profitability, which can be proxied by the difference between a capitalization rate and costs of funding. If a good timing to catch high profitability is foreseen, the newly completed offices will be released to market. Pre-let activities normally begin around two quarters before completion and this time is then used as a lag for the difference between cap and mortgage rates. Since supply in equilibrium is adjusted by structural vacancy, one-quarter lagged search effort level and mismatch rate are used to explain current supply.
As landlords can adjust the quantity of listed properties based on recent market developments and the current exogenous business environment, we expect the search effort level to be explained by one-quarter lagged real rent and office stock, as well as simultaneous real aggregate income. Similarly, for the economic mismatch rate, one-quarter lagged office stock and current exogenous conditions of real aggregate income and population are selected. Real market rents are not included in this equation because landlords deliberately retain a certain amount of vacant space to seek for opportunities of positive deviations from market rents.

Fixed Effects

In particular, the fixed time effect is not included in the rent equation since unobserved quarter specific constant terms should not be added. For the demand side, almost no characteristics are exactly the same across MSAs and share consistent time varying process. Even the corporate tax rate is nationwide, but remains virtually unchanged over time. Thus, we also omit the fixed time effect from this equation, but include it in all other equations. Since premier developers or landlords may invest across the US, their unobserved financial conditions determining office supply and the matching process can be captured by fixed quarter effects. Moreover, fixed MSA effects are used in all equations to capture any local characteristics.

Impact of Global Financial Crisis

The observation period spans throughout the Global Financial Crisis (GFC hereafter) which was triggered in the fourth quarter of 2007. Due to a tremendous and unprecedented change in business sentiment particularly in financial sectors, we attempt to investigate possible regime switching from the GFC by adding a post crisis period dummy (equal to 1 from 2007Q4 and zero otherwise) into all equations.

[1] We choose 12-quarter lags for panel A and 11-quarter lags for panel B.

We also use an alternative measure which is MSA-dependent. GFC Downturn is chosen (by the MSA) as the period with the lowest correlation between occupancy rates and real rents since 2007Q4.

Hurricane Effects

We limit to hurricanes originated from Atlantic Ocean only since those from Eastern Pacific Ocean are much less intense that do not cause any serious damage in accordance with track records starting from 1851 maintained by the National Hurricane Center. To address hurricane effects in office supply, we put dummies of hurricane threatened area and occurrence of hurricanes from Atlantic Ocean in the supply equation. We separate location and time dimension so as to proxy embedded hurricane risk from long history by MSA, and interaction terms between two dummies enhance flexibility to capture actual incidence. For the rent equation derived by the demand function, only the occurrence dummy is included to capture a temporary change in overall sentiment but we argue that to capture long term hurricane risk not considered by tenants is unnecessary (hence actual occurrence is not included). Finally, we assume that the matching process is insulated from a temporary natural hazard effect, and therefore no related dummies are added to the equations of economic mismatch and search effort level.

Effects of Lack of Transportation

Transportation infrastructure may be considered by developers or landlords in their supply function. We proxy for lack of transportation by residents' travel time to work. We identify an area with lack of transportation when the travelling time is one standard deviation bigger than the average. We capture this effect in the supply equation to conduct a robustness check on a possible multicollinearity arising from the relatively high correlation (around +0.4) between hurricane dummy and lack of transportation. Our results are not significantly affected.

Covering 43 MSAs, the system of long-run simultaneous equations including all effects highlighted above can be represented as follows:

$$
\begin{aligned}
ln(RRI_{l,t}) = d_0 + d_1 ln(S_{l,t-1}) + d_2 ln(EMI_{l,t-2} or INEMI_{l,t-2}) + d_3 ln(RII_{l,t-4}) + \\
d_4 MR_{l,t-1} + d_5 * PostCrisis + d_6 ATH_t + \sum_{n=7}^{49} d_n MSA \times ln(S_{l,t-1}) + \mu_{l,t}^{RRI}
\end{aligned} \tag{9}
$$

$$
\begin{aligned}
ln(S_{l,t}) = {} & e_0 + e_1 ln(RRI_{l,t-12}) + e_2 ln(ROPEXI_{l,t-12}) + e_3 SEL_{l,t-1} + \\
& e_4 MR_{l,t-1} + e_5 CM_{l,t-2} + e_6 * PostCrisisPeriod + e_7 ATH_t + e_8 HU_l + \\
& e_9 ATH_t \times HU_l + e_{10} ATH_t \times ln(RRI_{l,t-12}) + e_{11} HU_l \times ln(RRI_{l,t-12}) + \\
& e_{12} ATH_t \times HU_l \times ln(RRI_{l,t-12}) + \sum_{m=13}^{55} e_m MSA \times ln(RRI_{l,t-12}) + \mu^S_{l,t}
\end{aligned}
\tag{10}
$$

$$
\begin{aligned}
MR_{l,t} = {} & f_0 + f_1 ln(POP_{l,t-1}) + f_2 ln(EMI_{l,t-1}) + f_3 ln(RII_{l,t-1}) + f_4 ln(S_{l,t-1}) + \\
& f_5 * PostCrisis + \mu^{MR}_{l,t}
\end{aligned}
\tag{11}
$$

$$
SEL_{l,t} = g_0 + g_1 ln(RRI_{l,t-1}) + g_2 ln(S_{l,t-1}) + g_3 ln(RII_{l,t}) + g_4 * PostCrisis + \mu^{SEL}_{l,t}
\tag{12}
$$

Note: Please refer to Table 2 for notation.

Our aim is to estimate the long-run supply elasticity for each MSA. We compute it by adding coefficients e_1 to e_m of the corresponding MSA. In order to check the robustness of our model, we also compute demand elasticity by taking the reciprocal of the sum of d_1 and d_n of the corresponding MSA.

Since construction costs are in theory a crucial determinant of property supply, we investigate its actual impact empirically for 30 MSAs where construction cost data is available. Subsequently we discuss the opportunity of dropping this variable to extend our study to 42 MSAs in a latter section.

To capture short-run dynamics, we also construct four short-run equations in an Engle-Granger framework, which are also solved simultaneously. The coefficient for the error correction term indicates the quarterly percentage of adjustment of each dependent variable (i.e. real rent, office stock, search effort level and economic mismatch rate) to its long-run equilibrium. We expect coefficients to be negative and with an absolute value between 0 and 1.

$$
\begin{aligned}
\Delta ln(RRI_{l,t}) = {} & d_{50} + d_{51}\Delta ln(S_{l,t-1}) + d_{52}\Delta ln(EM_{l,t-2} or INEMI_{l,t-2}) + \\
& d_{53}\Delta ln(RII_{l,t-4}) + d_{54}\Delta MR_{l,t-1} + d_{55}\mu^{RRI}_{l,t-1} + \nu^{RRI}_{l,t}
\end{aligned}
\tag{13}
$$

$$\Delta ln(S_{l,t}) = e_{56} + e_{57}\Delta ln(RRI_{l,t-12}) + e_{58}\Delta ln(ROPEXI_{l,t-12}) + e_{59}\Delta SEL_{l,t-1} \\ e_{60}\Delta MR_{l,t-1} + e_{61}\Delta CM_{l,t-2} + e_{62}\mu^{S}_{l,t-1} + \nu^{S}_{l,t} \quad (14)$$

$$\Delta MR_{l,t} = f_6 + f_7\Delta ln(POP_{l,t-1}) + f_8\Delta ln(EMI_{l,t-1}) + f_9\Delta ln(RII_{l,t-1}) + \\ f_{10}\Delta ln(S_{l,t-1}) + f_{11}\mu^{MR}_{l,t-1} + \nu^{MR}_{l,t} \quad (15)$$

$$\Delta SEL_{l,t} = g_5 + g_6\Delta ln(RRI_{l,t-1}) + g_7\Delta ln(S_{l,t-1}) + g_8\Delta ln(RII_{l,t}) + g_9\mu^{SEL}_{l,t-1} + \nu^{SEL}_{l,t} \quad (16)$$

Capturing Likelihood of Change in Frictional Vacancy

Alongside our main model, which currently estimates structural vacancy assuming a negligible impact of frictional vacancy, we also construct another set of simultaneous systems to add the likelihood of change in frictional vacancy. We assume that physical mismatch is found in non-prime offices only when a major refurbishment is required to make the space characteristics meeting demand requirements. Landlords can either look for more affordable tenants to rent the existing non-prime quality space or upgrade the building to prime quality to earn higher rents and extend the economic life in the long-run. We assume that switching between physical and economic mismatch would occur at the "right" timing of refurbishment, which is one year long. We expect that the timing of refurbishment (and hence likelihood of change in frictional vacancy) depends on the rental gap between prime and non prime offices. We compile a dummy variable with value 1 when the gross asking rent for prime offices is 50% higher than the one for non-prime offices. In our model, we add an interaction term between the economic mismatch rate at time t and this dummy to proxy for the likelihood of economic mismatch switching to physical mismatch. We also add an interaction term between the four-quarter lagged dummy and current mismatch rate to proxy for the likelihood of physical mismatch turning to economic mismatch after refurbishment. A drawback in this approach is the need to use the current (rather than one-quarter lagged) economic mismatch rate to mitigate for the confusion of the lagged impact. Furthermore, the equation of mismatch rate also includes these dummies.

4.2 Dataset and Data Sources

We collect raw property data with a quarterly frequency from CBRE Econometric Advisors (CBRE EA hereafter; Torto Wheaton Research)[2], mortgage rate data from the Federal Reserve, hurricane information from the National Hurricane Center and structure cost data from the Lincoln Institute of Land Policy. Other demographic and economic data on population, aggregate personal income and employment base in the office sector are estimated by Moody's Analytics (formerly economy.com)[3] but also disseminated by CBRE EA.

To estimate the long-run supply elasticity of office markets using the mismatch model, we capture mismatch situations that are identified by available (i.e. listed for rental) but occupied space. Due to its availability starting only from the first quarter of 2005 for 43 MSAs which cover 47% of US population, a balanced panel dataset from the first quarter of 2005 to the fourth quarter of 2015 is used for this study. Construction cost data in 30 MSAs for the same period are also collected. We set up two datasets: panel A ignores construction structure costs and covers 43 MSAs; panel B includes construction costs but only covers 30 MSAs. If we exclude dummies, ten main variables are used in our model, four endogenous [real rent index ($RRI_{l,t}$), office stock ($S_{l,t}$), mismatch rate ($MR_{l,t}$) and search effort level ($SEL_{l,t}$)] and six exogenous [real construction structure cost index ($RSI_{l,t}$)[4], real operating expense index ($ROPEXI_{l,t}$), real aggregate personal income index ($RII_{l,t}$), difference between capitalization and mortgage rates ($CM_{l,t}$), employment index in the office using sectors ($EMI_{l,t}$) and population ($POP_{l,t}$)]. The variables are obtained as follows:

Real Rent Index ($RRI_{l,t}$). Nominal rent index are obtained from CBRE EA, which uses a hedonic modelling approach based on over 200,000 office leases on the basis of the non-discounted sum of all rental payments considering free rent periods but excluding tax. We deflate the nominal rent index using the Consumer Price

[2]CBRE EA, the independent research firm owned by CBRE which is one of the largest property consultancy firms in the US. They provide a comprehensive property market database to real estate investors. The database covers fundamental market and investment data at MSA level by property sectors which include apartment (61 MSAs), office (63 MSAs), retail (63 MSAs) and industrial (52 MSAs) properties. Basic data such as rent, stock, vacancy, completion, net absorption and capitalization rate are provided in every property sector. The database of the office sector is the most comprehensive in terms of time span of basic data starting from the second quarter of 1988 and greater depth of market data that availability rate, available but occupied space, total return, gross income and net operating income are exclusively compiled by CBRE based on information from property owners, despite some series are discontinuous.

[3]Economy.com has been the subsidiary of Moody's Analytics since 2005. They provide data and analysis on regional economies by country. Particularly in the US, labour markets, demographics, industries and other variables are offered at MSA level.

[4]It is used for panel B only.

Index (CPI) at the MSA level.
Mismatch Rate ($MR_{l,t}$). We identify **economic mismatch** using the "available but occupied stock", which indicates office space listed by landlords while it is still occupied. This variable suggests that the existing tenant is not prepared to pay the asking rent at renewal and there is no incentive for a major refurbishment to be carried out after the existing tenant moves out. If the landlord were intending to carry out a refurbishment - which would suggest the presence of a physical mismatch, the property would not be listed and made available for rental to new tenants. In our main model, the percentage of "available but occupied stock" is computed as the economic mismatch rate. As a robustness check, we also follow Cheshire et al (2016)[4] and compute the rate as the ratio between "available but occupied stock" and vacant stock. This ratio indicates the extent to which the economic mismatch can be accommodated by the currently vacant stock.
Search Effort Level ($SEL_{l,t}$). Non-transparent information may hinder the search and matching process: the less the information provided by landlords, the greater is the effort for tenants to search for the matching. Hence, we quantify the search effort level by using the ratio between:

- the difference between the maximum number of buildings with asking rents in any quarter of the last five years and the number of buildings with asking rents within the quarter, and

- the difference between maximum and minimum number of buildings with asking rents in any quarter of the last five years.

Real Construction Structure Cost Index ($RSI_{l,t}$). Construction costs of offices are estimated by multiplying ratios of structure cost to housing prices with office values. we deflate estimated costs with CPI at the MSA level. This estimation might be affected by difference of value growth between offices and housing.
Real Operating Expense Index ($ROPEXI_{l,t}$). Nominal operating expenses are yielded by subtracting net operating income and tax from gross income. We deflate the nominal index by using the CPI at the MSA level.
Real Aggregate Personal Income Index ($RII_{l,t}$). We deflate aggregate personal income earned by residents with CPI at the MSA level.
Cap Rate minus Mortgage Rate ($CM_{l,t}$). Capitalization rates exceeding the cost of funding signal the right timing for marketing nearly completed developments. Thus, we assume the existence of a positive relationship with office supply. Based on Wachter's finding(2016[36]), we assume the difference in rates as exogenous since credit markets misprice risk.

Employment Index ($EMI_{l,t}$). The employment base refers to the number of employees for financial and professional service industries. To standardize a comparable base across MSAs, we compile the employment index with base set in the fourth quarter of 2015. Furthermore, we use a same approach to create employment index for information industries ($INEMI_{l,t}$).

In addition, we construct five dummy variables to capture the effect of the global financial crisis (GFC), hurricane threat, lack of transportation for robustness check and likelihood of changes in frictional vacancy.

Post Crisis Period. We separate the sample into two periods (before and after the occurrence of the GFC, with the break point set on the fourth quarter of 2007) to capture the impact of the downturn caused by the most recent economic crisis. As a robustness check, we also include a dummy (**GFC Driven Downturn**) representing the period of the downturn which is obtained for each MSA identifying the lowest correlation between rent and occupancy rate.

Hurricane Threatened Area (HU_l): Tropical cyclones are casted from the Atlantic or East Pacific Ocean. Because most powerful hurricanes are originated in the former, we define the threatened MSAs (including neighboring areas) as the ones where at least one hurricane occurred within our sample period. According to the records from the National Hurricane Center, Baltimore, Cincinnati, Columbus, Fort Lauderdale, Houston, Indianapolis, Miami, Raleigh, Tampa, Trenton, West Palm Beach and Wilmington are selected among the MSAs we identify as HTA.

Atlantic Hurricane Occurrence (ATH_t): To compile this dummy, we track the dates of hurricanes occurrence (value of 1 if it occurs and 0 otherwise). The purpose of separating time and location dummies is to address both overall natural hazard risk and actual incidence through an interaction term.

Travel Time To Work ($TTWD_l$): We assume that travel time is time invariant and also take an average among MSAs. If residents in certain cities take time which is one standard deviation above average, the transportation infrastructure is regarded as insufficient.

Asking Rent Gap Between Prime and Non-prime Offices ($\geq 50\%$): Physically mismatched offices require a major refurbishment to avoid holding vacant space for long time periods. We assume this situation is limited to non-prime offices. Along with an extension to the economic life of a building, a major refurbishment also raises rents back to the ones asked for prime quality buildings. Therefore, a gross asking rent gap between prime and non-prime offices can be used as a proxy for the likelihood of exercising a refurbishment option. After refurbishment, the previous physical mismatch (i.e. frictional vacancy) turns into an economic match (if space is occupied) or mismatch (if still vacant). The gap between prime and secondary rents can signal the likelihood of changes in physical mismatch (the higher the gap the higher the incentive to refurbish), but it cannot directly identify the amount of physical mismatch or frictional vacancy. We assume that landlords of non-prime offices decide to refurbish if gross rents of prime offices are 50% higher than non-prime rents. The dummy variable has value 1 when the gap is above 50% and 0 otherwise.

Finally, to investigate the relationship between structural vacancy and supply elasticity, we use the components of our estimated long-run supply equation to estimate the structural vacancy as a composition of economic mismatch rate and search effort level, dividing the exponential of $[e_3 SEL_{l,t-1} + e_4 MR_{l,t-1}]$ by total supply (please refer to Equation 10).

4.3 Panel Unit Root and Cointegration Tests

To confirm the existence of short run dynamics, we conduct panel unit root and cointegration tests. Because of heterogeneous characteristics of property markets across MSAs, we select the Im-Pearson-Shin (IPS hereafter) panel unit root test and the Pedroni panel cointegration test in which we assume heterogeneous intercepts and trends. The IPS panel unit root test results confirm that all variables (except for real structure cost index i.e. I(0)) are integrated of order one - i.e. I(1) - as the residual series of the nine variables in their level and first difference are respectively non-stationary and stationary at 1% significant level[5]. In particular, since stock is accumulated and demolition rarely occurs, we assume that its non-stationarity is characterized as a deterministic trend process and hence a deterministic non-stationarity of $\ln(S_{l,t})$ is tested. We also prove that $\ln(S_{l,t})$ is an I(1) time series - please refer to Table 20 in the Online Appendix for a full set of results.
Since all variables satisfy the requirements of cointegration, we also conduct the residual-based Pedroni panel cointegration test for the four equations in our system and use seven statistics including four within-dimension-based (i.e. panel-ν, panel-ρ, semi-parametric panel-t (PP) and parametric panel-t (ADF)) and three between-dimension-based (i.e. group-ρ, semi-parametric group-t (PP) and parametric group-t (ADF)). Among all statistics, panel-ν and parametric group-t (ADF) have the highest and lowest power respectively[6]. The within-dimension based statistics are computed based on estimators that pool the autoregressive coefficient across different MSAs for the unit root tests on the estimated residuals. In contrast, the between-dimension-based statistics rely on estimators that average individually estimated

[5]The capture of I(0) variable would not affect co-integration among I(1) variables, therefore we cover real structure costs in the models.

[6]It refers to a proportion of times that the null hypothesis (i.e. no cointegration) is rejected when some or all time series in the panel are cointegrated.

coefficients for each MSA. All four equations show the rejection of the null of "no cointegration" (with the only exception of panel- and group-ρ) and therefore we can confirm the need to use an Engle-Granger based error correction model assuming a cointegration in the long-run and a short-run adjustment - please refer to Table 21 in the Online Appendix for a full set of these statistics.

We aim to examine the importance of search and matching theory by comparing the main models with others in which either or both variables $SEL_{l,t}$ and $MR_{l,t}$ are dropped. However in our empirical exercise, we could only drop $SEL_{l,t}$ simultaneously maintaining a cointegrated relationship in real rent to validate the error correction model. Thus, we build an alternative simultaneous system without required search effort for robustness check. In addition, our conclusion of cointegration is also supported by most test statistics being significant. To exercise the strictest rule, we also construct first difference models to analyze long-run relationships for robustness check and further comparison.

5 Estimation Results

We separate the estimation results into long-run relationships and short-run dynamics. However, we select the models for short-run dynamics in accordance with the suitability of the corresponding long-run simultaneous system.

5.1 Long Run Relationships

Before showing the main results, we discuss how real operating expenses represent a good proxy for construction costs because the inclusion of real construction costs alongside those expenses does not show any significance. We reduce the dataset to panel B which covers 30 MSAs but contains time series of the real construction cost index and employment in information industries - please refer to tables 22 to 25 in the Online Appendix for a full set of results. We find that one percent increase in real construction costs brings a minimal impact on office supply (i.e. +0.01%) with either general employment in office sector or information industries. Moreover, we proxy technological innovation at MSA level by employment in information industries assuming that a higher innovation leads to a higher depreciation of office properties. However, we found based on panel B that employment in office using sectors and in information industries have similar degree of impulses to real rent (i.e. +0.3 to +0.4%) under changes in nature of space demand driven by high technology industries. Therefore, we skip modelling by using real construction costs and employment in information industries in main models.

Returning to the main set of results, we construct six versions of our simultaneous system for panel A. To be consistent with our findings on heterogeneous trends across MSAs in panel unit root and cointegration tests, all versions include an interaction term between MSA dummies and supply (MSA x $\ln(S_{l,t-1})$) in the rent equation and between MSA dummies and real rents (MSA x $\ln(RRI_{l,t-12})$) in the supply equation. Since property market dynamics are usually localized due to supply constraints, this assumption is also in line with our objective function. Models M1 to M4 use the post crisis period dummy and differ for the inclusion of the aforementioned interaction terms between MSAs and lagged rent and supply in:

- equations of rent and supply only (M1);
- equations of rent, supply and economic mismatch rate (M2);
- equations of rent, supply and search effort level (M3);
- all four equations (M4).

Model M5 is similar to model M1 but the post crisis period dummy is replaced by GFC driven downturn. Finally, model M6 uses three equations only excluding the economic mismatch rate equation to test its significance in our system.

Real Rent

Table 3 exhibits the long-run relationship of real rents derived from the demand function. First four models show consistent results. The impact of an increase in supply is greater than the one of demand factors and economic mismatch: a 1% increase in supply reduces real rents by 2.8%-2.9%, while a 1% increase in real aggregate income or employment increases real rents by just 0.3%-0.4%; and a 1% increase in mismatch rate leads to a 0.7%-0.9% reduction in real rents. The coefficient of post crisis period is consistently high across models confirming the belief that the GFC has brought a significant change in office markets. Since the post crisis period covers trough and recovery, an increase in real rents is estimated. Furthermore, the occurrence of hurricanes originated in the Atlantic Ocean increases real rents (probably through a reduction in supply). Overall, statistically insignificant coefficients for the interaction terms in the economic mismatch equation in models M2 and M4 and the lowest Bayesian Information Criteria among models M1 to M4 suggest that model M1 is the preferred choice. Finally, distortion driven by interaction terms in the economic mismatch equation may occur in other systems. Similar circumstances are found when adding interaction terms with MSAs to model M3, but changes are opposite and more moderate. These may imply that the search and matching process does not have strong local factors. Comparing M1 with M5, results seem to suggest that real rents are actually (6.3%) higher rather than lower during the GFC driven downturn than in other periods. When downturn is captured in the model, moderately larger coefficients of other variables are also estimated, except for the occurrence of Atlantic hurricanes. Furthermore, the impact of economic mismatch turns weaker than fundamental demand factors (contradicting results found in model M1) and a 1% increase in supply now reduces real rent by only 1.9% (compared to 2.8% in M1). Since even a moderate growth in real rents is unrealistic during the downturn, we still prefer model M1 to M5.

[Insert Table 3 Here]

Office Stock

Table 4 summarizes the long-run relationship of office supply. Among the first four models, M3 and M4 estimate a coefficient of post crisis period, suggesting a significant increase in total supply after the GFC. Given that land costs remain low in that period, more development opportunities may have unfolded after the GFC. According to all first four models, a 1% increase in real rents leads to an increase in supply by 0.12%, while real operating expenses do not seem to influence supply at all (-0.01%). Relatively to real rents, the impact of the economic mismatch rate is similar (-0.1%) but with opposite sign, while a very small economic impact of search effort level is found. We use lagged difference between cap and mortgage rates to proxy for pre-let activities (to indirectly enhance the accuracy in measuring vacancy adjustments), which exert a minimal impact on overall supply (+0.01%).

Focusing on the hurricane effect, we use a three-way interaction term to estimate differential impacts. There are discrepancies in results among our models. We discuss results in M1 as it represents the model with best fit (see discussion above). For MSAs bearing hurricane risk, supply is about 80% less than others without hurricane risk. Whether we ignore or consider occurrence of hurricanes, a 1% increase in real rents in an area facing hurricane risk would lead to a 0.08% decrease in supply. Coupling with insignificant impacts of interactions between changes in real rent and hurricane occurrence, this implies that a long term hurricane risk and not only its occurrence may affect developers and landlords' decisions. By comparing M1 with M5, we conclude that replacing post crisis period with GFC driven downturn does not lead to inconsistent results for the impact of hurricane risk areas.

[Insert Table 4 Here]

Economic Mismatch and Search Effort Level

The equilibrium state of the search and matching process is represented by the long-run equations of economic mismatch rate and search effort level in Tables 5 and 6. The inclusion of interaction terms related to office supply and real rent in these two long run equations causes significant differences in the estimation results across models M2 M3 and M4. Because the search and matching process is unlikely to be heterogeneous across MSAs, the interaction of MSA dummies with office supply and/ or real rents may lead to over-identification. As a consequence, the results estimated in model M1 are found to be more reliable and plausible.

A 1% increase in office stock reduces the economic mismatch rate by 0.047 in value (i.e. linear-log relationship), corresponding to 1.01% drop if compared to its average value. A 1% increase in aggregate income leads to a decrease of 1.06%, while a 1% increase in city size (measured by population) brings the minimal impact (+0.43%) and a 1% increase in employment stimulates a 0.22% increase in mismatch rates. Furthermore, replacing post crisis period with downturn in M5 grants a coefficient consistent with theoretical predictions (i.e. downturn leads to 6.86% increase in mismatch rate) and other coefficients (except population) are similar to M1.

Search effort level is explained by real rents, office stock and real aggregate income at 1% significant level. A 1% rise in real rent and supply respectively reduces the search effort by 0.82% and 11.83%. In contrast, a 1% increase in real aggregate income increases the required search effort by 3.97%. Interestingly, we hereby find evidence of strategic games played by landlords who may wait for better deals to happen in the future, holding vacant space and hence increasing the search effort in periods of higher aggregate income. In addition, it is possible that more property offers listed in the market lead to a reduction in search effort instead of prolonging decision process to consider more choices. As shown in M5, the search effort is slightly eased by 0.23% during the downturn.

[Insert Table 5 Here]

[Insert Table 6 Here]

Importance of Search and Matching Process

Based on Pedroni test results, we cannot omit search effort level in the systems. The search effort level plays a dominant role of the search and matching process. The comparison between M6 and M1 reflects this phenomenon. Although there are no obvious differences, one more MSA records negative supply elasticity estimated by M6. With respect to Bayesian Information Criteria, M6 seems better fit. However, we would maintain the estimation of supply elasticity as precise as possible, M6 may not be the best performed because of more MSAs estimated with negative elasticity. Therefore, we could conclude that missing economic mismatch in the model may cause estimated supply elasticity being less precise. Furthermore, we have to capture the search and matching process to estimate supply elasticity.

Estimated Long Run Elasticity of Supply and Demand

We rely on coefficients of interaction terms for each MSA with lagged supply and real rent to estimate demand and supply elasticity by MSA. Based on the findings in model M1, the supply elasticity is estimated in the range between -0.163 and 0.377 while demand elasticity ranges between -40.575 and +0.304 and thends to be less left skewed than supply elasticity. We summarize our estimations of supply elasticity in a map (Figure 2) which show our geographical coverage (corresponding to an overall 47% of the entire US population). All office markets are supply inelastic and negative supply elasticity estimated in San Jose, Charlotte and San Francisco implies no response of supply to changes in real rents. Because of no zoning, Houston is the least inelastic.

As far as demand elasticity is concerned, four MSAs (Houston, Denver, Dallas and Pittsburgh) are demand elastic and the vast majority are demand inelastic. We find a surprising positive demand elasticity in San Francisco, which may reflect a "Veblen effect" (i.e. signalling theory) where wealthy individuals consume more when the price is higher so as to advertise their business and achieve a greater status (Baowell et al 1996[1]). San Francisco, as the best known CBD in West region, may actually exhibit its Grade A offices as Veblen goods. More than 60% of office space is prime quality graded and a relatively strong Veblen effect would influence the overall rent. At the same time, San Francisco is the most supply inelastic, suggesting the possibility that landlords in this market hold some vacant space to gain from a higher future rental income. This strategy may clearly coexist with the Veblen effect.

We also use panel dataset B to estimate elasticity in 30 MSAs. Comparing to estimations by the main model M1 for 42 MSAs, a range of supply elasticity is widened, but a narrower range is shown in demand elasticity. High correlation (+0.9) of estimates between models confirms the possibility of excluding real construction costs to expand our study to a bigger number of MSAs. We report all estimated elasticities in table 7.

[Insert Table 7 Here]

Likelihood of Changes in Frictional Vacancy

As for non-prime vacant space an economic mismatch can switch to a physical one and vice versa, a change in frictional vacancy may occur. To capture this switch, we add the condition that major refurbishment may be carried out in the equations of supply and economic mismatch in Panel A[7]. Since all other coefficients do not change significantly, we focus our attention on the results we obtain for the likelihood of frictional vacancy to occur and report the coefficients in Table 8. Following the previous process, we estimate five models (I1 to I5) with different combinations of the MSA interaction term with supply and mismatch rate and we do not report model 6.

For the supply equation, the likelihood of change in frictional vacancy increases the overall supply. The interaction term ($GRG50_{l,t} \times MR_{l,t}$) reflects a 0.5-0.6% reduction in the impact of the current economic mismatch, implying an increase in physical mismatch with space being refurbished. Assuming that refurbishment takes a year, the interaction term ($GRG50_{l,t-4} \times MR_{l,t}$) shows that refurbished space brings an insignificant positive adjustment to economic mismatch on supply. Although we are able to capture changes in frictional vacancy into the model, moderate alteration is found in coefficients of interaction terms between MSA and lagged real rent. This leads to moderate changes in estimated supply elasticity. As far as the mismatch rate equation is concerned, we do find evidence that the economic mismatch is lower when refurbishment options are more likely to be exercised and becomes higher after one year because physical mismatch may turn into an economic mismatch after the refurbishment takes place.

[Insert Table 8 Here]

5.2 Short Run Dynamics

Among all versions of the main simultaneous system, M1 is the best fit long run model. Therefore, we continue to build the short-run equation models from M1 but excluding fixed time and MSA effects. We present four versions of the same model with inclusion/ exclusion of post crisis period or occurrence of hurricanes from the Atlantic Ocean. Table 9 summarizes the short-run relationship of real rents. All four systems obtain results in line with theoretical predictions, where changes in supply and mismatch rate are negatively related and employment and aggregate income are positively related to changes in real rents. The coefficient of error correction term measures speed of adjustment and all models find that almost 14% of real rents is adjusted to equilibrium every quarter. In other words, full adjustment to equilibrium of real rents might take approximately 7.3 quarters. All models also obtain similar results for the short-run supply equation, which we report in Table 10. The speed

[7] Due to smaller sample sizes, we cannot conduct same analysis on Panel B.

of adjustment for office supply is lower than the one for rents as it is estimated to be around 12.3% per quarter, implying a full adjustment to equilibrium within 8.2 quarters.

[Insert Table 9 Here]
[Insert Table 10 Here]

Tables 11 and 12 summarize short run dynamics of the search and matching process. The speed of adjustment in the process is higher than for rents and supply. Particularly, 21.3% and 15.8% per quarter are adjusted in economic mismatch and search effort respectively. Hence, it takes a shorter period (4.7 and 6.3 quarters) to reach the long-run equilibrium. This may imply that landlords tend to control the search and matching process instead of responses to the market from development activities. Their strategy adjusts structural vacancy which determines adjusted office supply. If the speed of adjustment in adjusted supply is composed by vacancy adjustment and delivery speed of new development, the supply adjustment to equilibrium would be much slower than for the economic mismatch due to such low construction speed. We obtain related empirical evidence by estimating speed of adjustment for Panel dataset B. Referring to table 27 in online appendix, much lower speed to equilibrium is found in supply when models consider real construction costs (i.e. around 7.3% per quarter is adjusted). It takes 13.7 quarters to reach equilibrium. That means if landlords respond market shock by building new development, time period for adjustment will be prolonged.

[Insert Table 11 Here]
[Insert Table 12 Here]

Considering the likelihood of changes in frictional vacancy, similar results for the short-run models are found, with a slight increase in the speed of adjustment to long-run equilibrium in the supply equation (by 0.4 quarter).

5.3 Further Robustness Tests

First Difference Models and Mismatch Rate Measure

As a final step in our analysis we estimate models using first differences rather than levels. Clearly with this approach we are not able to separate long and short-run models. We start from the specification in model M1 and estimate six different specifications which we name R1 to R6 for panel dataset A. In the first four models (R1 to R4), the mismatch is quantified by the percentage of “available but occupied stock" while in the remaining two models (R5 and R6) the mismatch rate is computed as the ratio between "available but occupied stock" and vacant stock. Models R1 and R5 contain all four equations; R2 and R6 omit the equation of search effort level; R3 only excludes the mismatch rate equation; R4 removes both equations of mismatch and search effort level.

Overall, we find confirmation for the choice of a Engle Granger based ECM estimation using variables in levels. In fact first difference models show homogeneous trends across MSAs (i.e. coefficients for interaction terms are not significant in both rent and supply equations) when both theoretical predictions and previous findings in the literature suggest heterogeneity. Consistent results are obtained for models R1 to R4, with absolute changes in lagged supply and employment in the real rent equation moderately differ when we drop either/both mismatch or/and search effort level. Using the Bayesian information criterion in Table 13, R3 (excl. the mismatch rate) is the best-fit for first difference models. This result may imply that the search effort has a dominating role in the search and matching process. To test the robustness of our measure of mismatch rate, we compare the results in R1 and R2 models with respectively R5 and R6. Significant coefficients are similar in sign even if the magnitude sometimes changes. Some coefficients in the mismatch equation change sign but they are never significantly different from zero. Similar findings are obtained for panel dataset B.

[Insert Table 13 Here]
[Insert Table 14 Here]
[Insert Table 15 Here]
[Insert Table 16 Here]

Reduction of Gross Rental Gap for Models Analyzing Likelihood of Change in Frictional Vacancy

Instead of 50% gross rental gap dummy, we would also consider lower threshold (i.e. 40% gross rental gap) for models I1 to I5 based on real cases that landlords consider major renovations. By replacing the dummy GRG50 with the dummy GRG40, we found that the impact of current refurbishment on economic mismatch even more insignificant, in contrast, four-quarter lagged refurbishment reduces 0.5% of economic mismatch (17). This implies that refurbished properties attract tenants and eventually are rented to reduce mismatch. Regarding the equation of economic mismatch, 40% gross rental gap would not differ from previous results which are obtained in the models with 50% gross rental gap.

[Insert Table 17 Here]

Robustness Check on Hurricane Effects

Hurricane affected area may be port cities or old cities or cities which lack transportation infrastructure. In order to check if we are appropriate to capture hurricane effects, we insert dummies of port cities and old cities as well as a proxy for lack of transportation in the model M1. Since we capture hurricane effects in the equations of real rent and supply, we concentrate on these equations. Table 18 summarizes results of real rent equations. All three issues do not distort results of original models. However, partial results of supply equations would be affected by adding old cities into models referring to the model H3 in Table 19 - coefficient of hurricane affected area turns to positive sign but negative sign is showed on the dummy of old cities. The positive impact of hurricane threatened area seems unrealistic, therefore we conclude that, in general, original models could capture hurricane effects with appropriate identification.

[Insert Table 18 Here]

[Insert Table 19 Here]

Exogeneity Test On Error Term Of Search Effort Level

In order to avoid endogeneity with other equations, we would assume that error terms in the equation of search effort level as exogenous. To check if this assumption realistic, we conduct Hausman test and the results showed error term as exogenous. That means our assumption is appropriate.

Imposing Constraints For Avoiding Negative Supply Elasticity

We impose three constraints on three interaction terms of MSAs (Charlotte, San Francisco and San Jose) with lagged rents in the supply equation in order to avoid negative supply elasticity. Similar results are obtained although demand elasticity of Houston turns to positive. This indicates our models robust and reliable.

Robustness Check With Longer Time Series Data

For panel dataset A, we exclude the equation of economic mismatch and originally is used to analyze the data from 2005Q1 to 2015Q4. We extend time span from 1998Q1 to 2015Q4. Similar results are found in the equations of real rent, and required search effort, except that the impact of Global Financial Crisis is more insignificant. However, if we use this model to estimate supply elasticity, more than 10 MSAs have negative supply elasticity since signs of coefficients of search effort and difference in capitalization and mortgage rates as well as Atlantic hurricane occurrence are changed. This may suggest that the model with more historic data should be revised. We conclude that lagged terms would vary by the period we observe. Based on estimation of supply elasticity, our main models using 2005Q1 to 2015Q4 perform better.

6 Discussion

To justify our estimation of office supply elasticity in forty two MSAs, we should raise two questions:

(1) Do new CBDs likely emerge?

(2) How tight is the height restriction in existing CBDs?

The first question is linked to the existence of geographic constraints. Land availability determines the possibility of forming new CBDs. The Spearman's rank correlation between undevelopable area measured by Saiz (2010)[30][8] and our estimated office supply elasticity is -0.25 at 85% confidence level. Land scarcity reduces elasticity of both residential and commercial real estate supply. Among three MSAs with perfectly inelastic office supply, San Jose and San Francisco (refer to Panel B) contains more than 50% of undevelopable area. Furthermore, Ventura (one of top 10 supply inelastic MSAs) with a supply elasticity of 0.015 contains the most undevelopable area - almost 80%. All of them are coastal cities that imply geographic constraints driven by the Pacific Ocean. The coastal barrier is also supported by Rose's finding (1989)[28] which was obtained with a different approach to measure the area net of water bodies. As a result, to develop new CBDs to replenish office supply is unlikely feasible.

Since the topology is not the only a source of supply constraints, Charlotte and Baltimore, with almost no natural barriers, show perfectly (or very) inelastic office supply. Extremely strong monopoly zoning power stored in these MSAs deters the supply response. Based on three calibrations of monopoly power of zoning governments including two concentration ratios of four largest suburb urbanization area and counts of zoning governments conducted by Rose (1989), these MSAs retain the greatest monopoly zoning power which crucially determines tightness of height restrictions or redevelopment. In contrast, more than 200 zoning governments are involved in New York City, Chicago and Philadelphia and low concentration ratios are also seen in Columbus, Los Angeles and St Louis. Relatively less inelastic supply elasticity is estimated in their office markets (except for New York City due to stricter height restriction discussed below). Therefore, the strength of monopoly zoning power gives responses to both our questions.

"Regulatory shadow tax" is an alternative approach to proxy for the tightness of regulatory constraints specifically driven by building height restrictions and it directly responds to our second question. Bertaud and Brueckner (2005)[3]; Glaeser et al (2005)[14] and Cheshire and Hilber (2008)[5] claim that height restrictions imposed

[8] Saiz(2010) estimates the area within the cities' 50-kilometer radii corresponding to wetlands, lakes, rivers or other internal water bodies to quantify land availability.

by governments minimize externalities and the difference in price setting between regulated and unregulated markets (i.e. price minus marginal cost of construction) can be used to quantify the degree of restrictions so called "regulatory tax". Glaeser et al (2005)[14] investigate height restrictions in housing markets in the US and find that zero regulatory taxes are present in some cities (e.g. Houston, Detroit, Pittsburgh, Philadelphia and Tampa) and they measure constraints of the office market in Manhattan only (i.e. 0 in trough period and 0.5 in peak period). However, these estimates may not be used to explain our office supply elasticity because the gap between market price and marginal cost is sometimes explained by the monopoly power held by developers in industries that are not very competitive. Cheshire and Hilber (2008)[5] analyze office markets in Britain and adopt a similar approach to quantify regulatory tax due to height restriction and find that regulatory constraints in London are much tighter than in Manhattan. We assume regulatory taxes in office markets are positively proportional to housing markets, and therefore deduce that height restrictions in the US could be weaker than those in London.
Differentiation of supply elasticity across MSAs is somewhat attributed to competition between states or cities driven by the incentives to local government revenues. Since sale and individual income taxes are the most important sources of state government revenues, governments are motivated to develop cosmopolitan CBDs to attract highly skilled residents. Rivalry among neighbouring state governments may exist and regulatory constraints of office space supply may be weaker in states with higher CBD status. For instance, human capital in Philadelphia is less well educated than in New York and Boston because of a disincentive of high tax rates (Gyourko et al 2005)[16]. High mobility causes firms choosing their location in highly competitive cities. Glaeser (2005)[13] also concludes that Boston is the most skilled city. If local governments in Philadelphia want to enhance the city competitiveness to attract both firms and talents, they may relax constraints on supply of commercial real estate to a certain degree. This implies relative less inelastic supply in Philadelphia comparing with New York and Boston. Overall, we find that regulatory constraints may be moderately adjusted based on fiscal condition of local governments.

7 Conclusion

Our research contributes to the studies related to supply constraints in two ways. Firstly, we build a conceptual framework distinguishing between physical and economic mismatch to obtain an estimation of frictional and structural vacancy as main components of the natural vacancy rate similarly to the labour market literature. Secondly, we adopt an empirical strategy which allows us to distinguish between long-run and short-run and obtain supply elasticity at MSA level that are correlated with the ones found in previous studies for housing markets. Particularly, our estimations are highly correlated with Wharton's residential regulatory constraints and housing supply elasticity measured by Saks and Wheaton separately (Refer to Table 1). We conclude that all office markets in forty two MSAs are supply inelastic, with San Jose, Charlotte, San Francisco(refer to Panel A) and Denver(refer to Panel B) showing a perfectly inelastic supply that could be explained by land unavailability and monopoly zoning power. In contrast, MSAs without zoning such as Houston and Tampa show a relatively high supply elasticity, although still below one. Moreover, a Veblen effect is found in San Francisco, which could coexist with the presence of landlords strategically holding vacant space to seek for higher future rents. To achieve precise estimations, we identify economic mismatch by observing occupied space which is listed to be re-leased (i.e. signalling a mismatch with an existing tenant). Further, we build the model to link the search and matching process with a framework of fundamental real estate cycle. The empirical strategy is not limited to estimate supply and demand elasticity, but it also attempts to estimate structural vacancy rates simultaneously.

So far our estimated structural vacancy and supply elasticity are positively correlated (Spearman rank correlation of +0.27) and we may interpret the relationship as follows: the low controlling power of landlords reduces the flexibility in adjusting equilibrium vacancies to respond to market shocks and this result may suggest that supply elasticity is almost completely explained by regulatory and geographical constraints. Landlords' controlling power would vary over boom and bust periods - in a boom period controlling power would be stronger than that in a bust period. Hence, hoarding may more likely occur in a boom period. In addition, we attempt to capture the likelihood of change in frictional vacancy in our empirical strategy and obtain results consistent with initial estimations excluding this factor and in line with theoretical predictions. Finally, the addition of frictional vacancy to the empirical model may improve our existing strategy as we may be able to deliver insightful research on the linkage between supply constraints and specific types of vacancy (i.e. structural and frictional) sequentially.

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Table 1: Spearman Rank Correlation Matrix of Supply Elasticity between Housing and Offices in the US

	WRLURI	**Saks**	**Green**	**Saiz**	**Wheaton(LR)**	**Office(With RSI)**	**Office (Without RSI)**
WRLURI	1						
Saks	0.552***	1					
Green	0.357**	0.511***	1				
Saiz	0.545***	0.613***	0.627***	1			
Wheaton(LR)	0.435***	0.368**	0.331**	0.37***	1		
Office(With RSI)	0.473**	0.365*	0.103	0.223[a]	0.247[b]	1	
Office(Without RSI)	0.427***	0.45***	0.257	0.24#	0.434***	0.916***	1

Notes: WRLURI and Saks are regulation indices measured by number of standard deviation of regulatory restrictiveness in housing markets (greater value indicates looser regulation), others estimate housing supply elasticity. For Saiz index, supply elasticity is presented in 2 decimal places. Data is slightly adjusted by extrapolation when same figures are shown but in different ranks. LR denotes "Long Run" elasticity respectively. Signs ***, ** and * as well as # represent significant results at 1%, 5%, 10% and 20% level respectively.

a: p=0.27; b: p=0.21.

Table 2: Data Summary Statistics

		Panel A						Panel B	
Acronym	**Variable**	**Mean**	**S.D.**	**Min.**	**Max.**	**Skewness**	**Kurtosis**	**Mean**	**S.D.**
$RR_{l,t}$	Real Rent (USD in 2015Q4 price)	24.163	8.068	14.739	81.984	3.144	17.307	24.679	9.226
$RRI_{l,t}$	Real Rent Index (2015Q4=100)	101.31	13.205	58.343	158.271	0.447	4.705	98.893	11.788
$S_{l,t}$	Office Stock (million sqf)	78.823	85.651	4.799	491.34	2.867	12.515	99.398	94.768
$MR_{l,t}$	$^{(a)}$ Economic Mismatch Rate (%)	4.668	1.719	0.739	12.274	0.228	3.229	4.569	1.579
$SEL_{l,t}$	$^{(b)}$ Search Effort Level	0.365	0.374	0	1	0.624	1.812	0.361	0.376
$ROPEXI_{l,t}$	$^{(c)*}$ Real Operating Expense Index (2015Q4=100)	97.157	19.655	6.547	278.222	3.213	29.088	94.893	14.13
$RSI_{l,t}$	$^{(d)*}$Real Structure Cost Index (2015Q4=100)							89.797	21.281
$RII_{l,t}$	$^{(e)*}$ Real Personal Income Index (2015Q4=100)	88.799	6.312	64.314	100.192	-0.737	3.691	88.002	6.206
$CM_{l,t}$	$^{(f)*}$ Capitalization Minus Mortgage Rate (%)	1.163	1.27	-2.157	4.527	-0.216	2.385	1.2	1.303
$EM_{l,t}$	* Employment in Office Using Sectors ('000 person)	358.789	302.112	51.7	1752.3	2.333	9.324	440.815	324.544
$EMI_{l,t}$	* Corresponding Employment Index (2015Q4=100)	92.21	7.306	63.855	108.2	-0.997	4.17	91.66	6.813
$INEMI_{l,t}$	* Information Industry Employment (2015Q4=100)	103.846	21.643	45.542	265.714	2.941	20.867	104.94	23.805
$POP_{l,t}$	* Population ('000 person)	3331.574	2601.41	361.9	14445.9	2.216	8.462	4069.337	2761.04
HU_l	* Hurricane Threatened Area	0.209	0.407	0	1	1.429	3.042	0.233	0.423
ATH_t	* Atlantic Ocean Hurricane Occurrence	0.523	0.5	0	1	-0.091	1.008	0.523	0.5
$TTWD_l$	* Dummy for Travel Time to Work	0.14	0.347	0	1	2.081	5.329	0.133	0.34
$GRG50_{l,t}$	$^{(g)}$ Asking Rent Gap $\geq$ 50% (Prime vs Non-Prime)	0.031	0.172	0	1	5.445	30.652	0.031	0.172
$SV_{l,t}$	Estimated Structural Vacancy Rate (%)	2.663	2.883	0.2	20.471	3.501	17.66	1.668	0.98

Notes: All statistics are based on a sample of 1892 panel observations (44 quarters by 43 MSAs) for each variable (except RSI). (a) This indicates preference of landlords to letting the property to new tenants instead of existing tenants and is identified by rate of available but occupied stock. We define this situation as "economic mismatch" since by intuition landlords search for new tenants only when existing rent paid by current tenants is lower than their desired level. (b) Search effort level is calculated as difference between maximum number of buildings in which asking rents are reported to CBRE over last 5 years and current number of reports divided by difference between maximum and minimum number of reports over last 5 years. (c) Before deflating with consumer price index (CPI), operating expenses are estimated by subtracting net operating income and tax from gross income. (d) We obtain the ratios of residential structure costs to house prices for 30 MSAs and estimate real construction costs of office buildings by multiplying these ratios with office values. However, we notice that difference in growth of prices between housing and offices may misestimate construction costs of office buildings. (e) Aggregate personal income earned by residents are deflated with CPI. (f) This identifies that investment opportunities with leverage in office sectors are suitable to market. Positive gap implies that capitalization rate is greater than cost of fund. (g) The rent gap is the main criteria for landlords who own non-prime offices exercising refurbishment options in addition of refurbishment costs. If prime rents far exceed non-prime rents, landlords are motivated to renovate physical mismatched property and hence reduce leading frictional vacancy. This condition is captured into the model in order to mitigate distortion of structural vacancy by change in frictional vacancy, however cannot be used for identifying frictional vacancy that is unlike structural vacancy which can be identified by search and matching adjusted stock. * indicates exogenous variables (all others are endogenous).

Table 3: Panel A: Long Run Relationship of Real Rent ($\ln(RRI_{l,t})$)

Independent Variable	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
Constant	omit	16.848***	omit	omit	9.689***	omit
		(2.581)			(2.432)	
ln($S_{l,t-1}$)[a]	-2.814	-2.88	-2.814	-2.918	-1.862	-3.078
ln($EMI_{l,t-2}$)	0.406***	0.399***	0.409***	0.401***	0.635***	0.433***
	(0.056)	(0.056)	(0.057)	(0.056)	(0.055)	(0.057)
ln($RII_{l,t-4}$)	0.271***	0.264***	0.272***	0.266***	0.415***	0.296***
	(0.071)	(0.071)	(0.071)	(0.071)	(0.067)	(0.071)
$MR_{l,t-1}$	-0.007***	-0.009***	-0.007***	-0.008***	-0.005***	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
Post Crisis Period	16.085***	omit	15.909***	16.669		17.04***
	(2.571)		(2.575)	(2.583)		(2.588)
GFC Driven Downturn					0.063***	
					(0.004)	
ATH	0.008***	0.008***	0.008***	0.008***	0.003#	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Fixed MSA Effect	Y	Y	Y	Y	Y	Y
F-Stat	135114	61.62	135114	135114	72.4	135705
BIC - Simultaneous System	-8053	-8044	-8017	-8002	-8210	-12123
R-sq	0.79	0.79	0.79	0.79	0.82	0.79
Observation	1376	1376	1376	1376	1376	1376

Notes: (a) Median values. Signs ***, **, * and # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 4: Panel A: Long Run Relationship of Office Supply ($\ln(S_{l,t})$)

Independent Variable	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
Constant	4.218***	4.213***	omit	omit	4.21***	omit
	(0.117)	(0.117)			(0.118)	
ln$(RRI_{l,t-12})^a$	0.123	0.124	0.119	0.12	0.129	0.126
ln$(ROPEXI_{l,t-12})$	-0.008***	-0.008***	-0.008***	-0.008***	-0.007***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$SEL_{l,t-1}$	-0.011***	-0.011***	-0.01***	-0.01***	-0.011***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$MR_{l,t-1}$	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	
$CM_{l,t-2}$	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post Crisis Period	omit	omit	4.2333***	4.229***		4.228***
			(0.118)	(0.118)		(0.117)
GFC Driven Downturn					0.004**	
					(0.001)	
ATH	omit	0.039**	omit	omit	omit	omit
		(0.02)				
HU_l	-1.65***	0.013	0.023	0.026	-1.647***	-1.638***
	(0.215)	(0.204)	(0.204)	(0.204)	(0.216)	(0.216)
ATH $\times$ HU_l	0.016	0.016	0.016	0.016	0.014	0.019
	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)
ATH $\times$ **ln**$(RRI_{l,t-12})$	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$HU_l\times$ **ln**$(RRI_{l,t-12})$	-0.233***	-0.229***	-0.231***	-0.233***	-0.232***	-0.216***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
ATH $\times HU_l\times$ **ln**$(RRI_{l,t-12})$	-0.003	-0.003	-0.003	-0.003	-0.003	-0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fixed MSA Effect	Y	Y	Y	Y	Y	Y
Fixed Time Effect	Y	Y	Y	Y	Y	Y
F-Stat	84289	84289	1.94×10^6	1.94×10^6	83649	1.95×10^6
R-sq	0.99	0.99	0.99	0.99	0.99	0.99
Observation	1376	1376	1376	1376	1376	1376

Notes: (a) Median values. Signs ***, **, * and # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 5: Panel A: Long Run Relationship of Mismatch Rate ($MR_{l,t}$)

Independent Variable	**M1**	**M2**	**M3**	**M4**	**M5**
Constant	-20.456#	298.362***	-20.724#	omit	-20.864#
	(14.624)	(51.806)	(14.625)		(14.613)
ln($S_{l,t-1}$)	-4.724**	-21.582[a]	-4.718**	-21.198[a]	-4.608**
	(1.978)		(1.978)		(1.977)
ln($RII_{l,t-1}$)	-4.93***	-7.448***	-4.891***	-7.428***	-4.936***
	(1.382)	(1.586)	(1.383)	(1.587)	(1.382)
ln($EMI_{l,t-1}$)	1.044	3.578**	0.986	3.432**	1.366
	(1.128)	(1.47)	(1.128)	(1.471)	(1.132)
ln($POP_{l,t-1}$)	2.025***	1.243	7.565***	1.621	7.302***
	(2.025)	(3.757)	(2.026)	(3.761)	(2.024)
Post Crisis Period	omit	omit	omit	295.052***	
				(51.856)	
GFC Driven Downturn					0.32***
					(0.12)
MSA Dummy × **ln**($S_{l,t-1}$)	N	Y	N	Y	N
Fixed MSA Effect	Y	Y	Y	Y	Y
Fixed Time Effect	Y	Y	Y	Y	Y
F-Stat	32.25	27.73	32.24	536.67	31.97
R-sq	0.64	0.7	0.64	0.7	0.64
Observation	1376	1376	1376	1376	1376

Notes: (a) Median values. Signs ***, ** and * represent significant level at 1%, 5% and 10% respectively.

Table 6: Panel A: Long Run Relationship of Search Effort Level ($SEL_{l,t}$)

Independent Variable	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
Constant	omit	omit	omit	omit	15.932***	15.956***
					(1.935)	(1.947)
ln($RRI_{l,t-1}$)	-0.298***	-0.295***	1.061^{a}	1.092^{a}	-0.364***	-0.294***
	(0.106)	(0.106)			(0.106)	(0.106)
ln($S_{l,t-1}$)	-4.317***	-4.309***	-4.678^{a}	-4.51^{a}	-4.265***	-4.314***
	(0.401)	(0.401)			(0.399)	(0.401)
ln($RII_{l,t}$)	1.448***	1.443***	0.862***	0.871***	1.495***	1.45***
	(0.229)	(0.229)	(0.282)	(0.282)	(0.227)	(0.229)
Post Crisis Period	16.0002***	15.97***	15.557	14.366		omit
	(1.946)	(1.946)	(14.2)	(14.199)		
GFC Driven Downturn					-0.083***	
					(0.025)	
MSA dummy × ln($S_{l,t-1}$)	N	N	Y	Y	N	N
MSA dummy × ln($RRI_{l,t-1}$)	N	N	Y	Y	N	N
Fixed MSA Effect	Y	Y	Y	Y	Y	Y
Fixed Time Effect	Y	Y	Y	Y	Y	Y
F-Stat	138.9	138.88	106.52	106.49	64.71	64.79
R-sq	0.78	0.78	0.86	0.86	0.78	0.78
Observation	1376	1376	1376	1376	1376	1376

Notes: (a) Median values. Signs ***, ** and * represent significant level at 1%, 5% and 10% respectively.

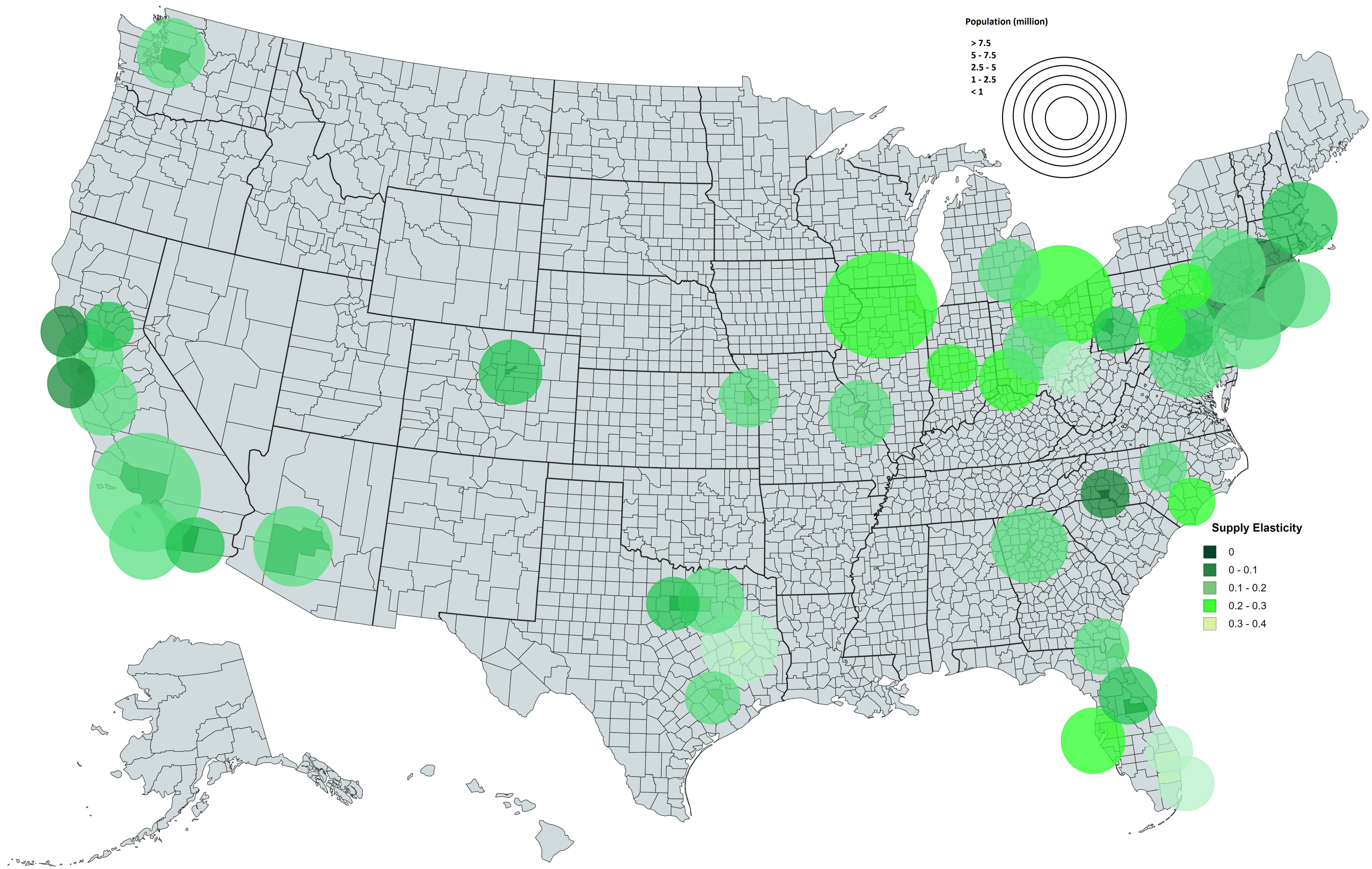

Figure 2: Map Chart of Supply Elasticity in 42 MSAs

Table 7: Estimates of Long Run Supply and Demand Elasticity of the Office Market by MSA

Model	Include RSI		Exclude RSI	
MSA	**Supply**	**Demand**	**Supply**	**Demand**
San Jose	-0.175***	-0.521#	-0.163***	-0.53*
Charlotte	-0.173***	-0.808***	-0.144***	-0.695***
San Francisco	0.148	0.47***	-0.026***	0.304***
New York			0.002***	-0.293
Denver	-0.025***	-1.691***	0.006***	-2.355***
Pittsburgh	0.037***	-0.97**	0.014***	-1.052***
Ventura			0.015***	-0.264#
Phoenix	0.018***	-0.406	0.02***	-0.355
Seattle	0.008***	-0.501	0.029***	-0.493#
Boston	0.019***	-0.413	0.039***	-0.457
Baltimore	0.075***	-0.617**	0.055**	-0.592**
Orlando			0.062***	-0.285
San Diego	0.075***	-0.238**	0.062***	-0.252#
Sacramento	0.064***	-0.302	0.065***	-0.276
Fort Worth	0.08**	-0.769**	0.07*	-0.876***
Orange County			0.079***	-0.115***
Los Angeles	0.1**	-0.242*	0.095*	-0.245
Newark			0.1*	-0.115***
Dallas	0.131	-1.047***	0.113	-1.903***
Washington, DC	0.083#	-0.59*	0.118	-0.611**
Jacksonville			0.119	-0.358
Long Island			0.128	-0.176**
Oakland	0.112*	-0.205**	0.129	-0.19*
Cleveland	0.148	-0.252*	0.137	-0.238#
St. Louis	0.144	-0.426	0.139	-0.366
Kansas City	0.167	-0.275#	0.141	-0.256
Philadelphia	0.328**	-0.588	0.142	-0.541
Atlanta	0.178***	-0.382***	0.15***	-0.338***
Austin			0.152	-0.646**
Raleigh			0.159	-0.451
Detroit	0.204	-0.049***	0.167	-0.045***
Stamford			0.201#	-0.235
Trenton			0.202	-0.842***
Columbus	0.314***	-0.271#	0.238***	-0.288
Indianapolis	0.309***	-0.342	0.242***	-0.292
Chicago	0.465***	-0.385	0.26***	-0.36
Cincinnati	0.359***	-0.337	0.275***	-0.292
Tampa	0.345***	-0.388	0.284***	-0.318
Wilmington			0.288***	-0.164***
West Palm Beach			0.309***	-0.683**
Fort Lauderdale			0.363***	-0.299
Houston	0.483***	-13.043***	0.377***	-40.575***

Notes: Negative value in supply elasticity is interpreted as no response of supply to change in office rent. Signs ***, ** and * as well as # represent significant levels at 1%, 5%, 10% and 20% respectively.

Table 8: Panel A: Long Run Relationships - Considering Likelihood of Change in Frictional Vacancy

Independent Variable	**I1**	**I2**	**I3**	**I4**	**I5**
Supply Equation(ln($S_{l,t}$))					
$MR_{l,t}$	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GRG50	0.043***	0.043***	0.043***	0.044***	0.043***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
GRG50 $\times MR_{l,t}$	-0.005***	-0.006***	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$GRG50_{l,t-4}$	0.006	0.006	0.006	0.006	0.006
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$GRG50_{l,t-4} \times MR_{l,t}$	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MSA dummy $\times$ **ln**($RRI_{l,t-12}$)	Y	Y	Y	Y	Y
F-Stat	2.01×10^6	2.01×10^6	87324	87324	86629
R-sq	0.99	0.99	0.99	0.99	0.99
Mismatch Rate Equation($MR_{l,t}$)					
$GRG50_{l,t}$	-0.228	-0.377**	-0.226	-0.362**	-0.247
	(0.177)	(0.178)	(0.177)	(0.178)	(0.177)
$GRG50_{l,t-4}$	0.472***	0.21	0.472***	0.22	0.458***
	(0.176)	(0.17)	(0.176)	(0.17)	(0.176)
MSA dummy $\times$ **ln**($S_{l,t-1}$)	N	Y	N	Y	N
F-Stat	32.29	531.76	677.27	531.72	31.99
R-sq	0.64	0.7	0.64	0.7	0.64
Fixed MSA Effect	Y	Y	Y	Y	Y
Fixed Time Effect	Y	Y	Y	Y	Y

Note: Signs ***, ** and * represent significant level at 1%, 5% and 10% respectively.

Table 9: Panel A: Short Run Relationship of Real Rent ($\Delta ln(RRI_{l,t})$)

Independent Variable	**M1a**	**M1b**	**M1c**	**M1d**
Constant	-0.004***	omit	-0.009***	omit
	(0.001)		(0.001)	
$\Delta ln(S_{l,t-1})$	-0.161#	-0.161#	-0.114	-0.114
	(0.113)	(0.113)	(0.111)	(0.111)
$\Delta ln(EMI_{l,t-2})$	0.445***	0.445***	0.47***	0.47***
	(0.051)	(0.051)	(0.05)	(0.05)
$\Delta ln(RII_{l,t-4})$	0.184***	0.184***	0.169***	0.169***
	(0.033)	(0.033)	(0.033)	(0.033)
$\Delta MR_{l,t-1}$	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$ECT^{RRI}_{l,t-1}$	-0.137***	-0.137***	-0.135***	-0.135***
	(0.011)	(0.011)	(0.011)	(0.011)
Post Crisis Period		-0.004***		-0.009***
		(0.001)		(0.001)
ATH			0.008***	0.008***
			(0.001)	(0.001)
F-Stat	81.17	73.85	80.94	74.95
Bayesian Information Criterion	-17099	-17099	-17146	-17146
R-sq	0.22	0.22	0.26	0.26
Observation	1333	1333	1333	1333

Notes: Bayesian Information Criterion measures suitability of the entire simultaneous system. Signs ***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 10: Panel A: Short Run Relationship of Office Stock ($\Delta ln(S_{l,t})$)

Independent Variable	**M1a**	**M1b**	**M1c**	**M1d**
Constant	0.003***	omit	0.002***	omit
	(0.0001)		(0.0002)	
$\Delta ln(RRI_{l,t-12})$	0.023***	0.023***	0.023***	0.023***
	(0.006)	(0.006)	(0.006)	(0.006)
$\Delta ln(ROPEXI_{l,t-12})$	0.01***	0.01***	0.01***	0.01***
	(0.002)	(0.002)	(0.002)	(0.002)
$\Delta SEL_{l,t-1}$	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta MR_{l,t-1}$	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.000)
$\Delta CM_{l,t-2}$	0.001**	0.001**	0.001**	0.001**
	(0.0003)	(0.0003)	(0.0003)	(0.000)
$ECT^S_{l,t-1}$	-0.123***	-0.123***	-0.122***	-0.122***
	(0.013)	(0.013)	(0.013)	(0.013)
Post Crisis Period		0.003***		0.002***
		(0.0001)		(0.0002)
ATH			0.0004#	0.0004#
			(0.0002)	(0.0002)
F-Stat	24.34	73.49	21.25	64.91
R-sq	0.1	0.1	0.1	0.1
Observation	1333	1333	1333	1333

Note: Signs ***, **, * and # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 11: Panel A: Short Run Relationship of Mismatch Rate ($\Delta MR_{l,t}$)

Independent Variable	**M1a**	**M1b**	**M1c**	**M1d**
Constant	0.059**	omit	0.059**	omit
	(0.027)		(0.027)	
$\Delta ln(S_{l,t-1})$	-4.846#	-4.846#	-4.916#	-4.916#
	(3.333)	(3.333)	(3.332)	(3.332)
$\Delta ln(RII_{l,t-1})$	1.077	1.077	1.029	1.029
	(0.984)	(0.984)	(0.984)	(0.984)
$\Delta ln(EMI_{l,t-1})$	-8.245***	-8.245***	-8.224***	-8.224***
	(1.517)	(1.517)	(1.517)	(1.517)
$\Delta ln(POP_{l,t-1})$	14.368*	14.368*	14.371*	14.371*
	(8.572)	(8.572)	(8.569)	(8.569)
$ECT^{MR}_{l,t-1}$	-0.213***	-0.213***	-0.213***	-0.213***
	(0.017)	(0.017)	(0.017)	(0.017)
Post Crisis Period		0.059**		0.059**
		(0.027)		(0.027)
F-Stat	35.36	33.35	35.36	33.35
R-sq	0.12	0.12	0.12	0.12
Observation	1333	1333	1333	1333

Note: Signs ***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 12: Panel A: Short Run Relationship of Search Effort Level ($\Delta SEL_{l,t}$)

Independent Variable	**M1a**	**M1b**	**M1c**	**M1d**
Constant	0.028***	omit	0.028***	omit
	(0.004)		(0.004)	
$\Delta ln(RRI_{l,t-1})$	0.138	0.138	0.138	0.138
	(0.134)	(0.134)	(0.135)	(0.134)
$\Delta ln(S_{l,t-1})$	-2.239***	-2.239***	-2.278***	-2.278***
	(0.632)	(0.632)	(0.632)	(0.632)
$\Delta ln(RII_{l,t})$	0.317*	0.317*	0.285#	0.285#
	(0.18)	(0.18)	(0.18)	(0.18)
$ECT^{SEL}_{l,t-1}$	-0.158***	-0.158***	-0.158***	-0.158***
	(0.017)	(0.017)	(0.017)	(0.017)
Post Crisis Period		0.028***		0.028***
		(0.004)		(0.004)
F-Stat	26.36	33.14	26.56	33.16
R-sq	0.08	0.08	0.08	0.08
Observation	1333	1333	1333	1333

Note: Signs ***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 13: Panel A: First Difference Models of Long Run Relationships: Real Rent

Independent Variable	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**
$\Delta ln(S_{l,t-1})^a$	0.044	0.049	0.099	0.095	0.068	0.061
$\Delta ln(EMI_{l,t-2})$	0.583***	0.583***	0.59***	0.59***	0.593***	0.593***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
$\Delta ln(RII_{l,t-4})$	0.199***	0.199***	0.2***	0.2***	0.203***	0.203***
	(0.034)	(0.034)	(0.033)	(0.034)	(0.034)	(0.034)
$\Delta MR(1)_{l,t-1}$	-0.001	-0.001				
	(0.001)	(0.001)				
$\Delta MR(2)_{l,t-1}$					0.0003**	0.0003**
					(0.0001)	(0.0001)
Post Crisis Period	-0.009**	-0.009**	-0.009**	-0.009**	-0.009**	-0.009**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ATH	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fixed MSA Effect	Y	Y	Y	Y	Y	Y
F-Stat	4.45	4.45	4.48	4.48	4.5	4.49
BIC - Simultaneous System	-14960	-13325	-17771	-16146	-9387	-7760
R-sq	0.21	0.21	0.21	0.21	0.22	0.22
Observation	1333	1333	1333	1333	1333	1333

Notes:
(a) Median values.
MR(1) is the mismatch rate computed by (available but occupied stock / total stock). MR(2) is the mismatch rate computed by (available but occupied stock / vacant stock).
***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.
Constant term is omitted in all models. All interaction terms in real rent equations are insignificant.

Table 14: Panel A: First Difference Models of Long Run Relationships: Office Stock

Independent Variable	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**
$\Delta ln(RRI_{l,t-12})^a$	-0.01	-0.011	-0.007	0.0004	-0.013	0.001
$\Delta ln(ROPEXI_{l,t-12})$	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\Delta SEL_{l,t-1}$	-0.0001		0.0001		3×10^{-6}	
	(0.001)		(0.001)		(0.001)	
$\Delta MR(1)_{l,t-1}$	-0.0003#	-0.0003#				
	(0.0002)	(0.0002)				
$\Delta MR(2)_{l,t-1}$					-0.0001**	-0.0001***
					(0.00002)	(0.00002)
$\Delta CM_{l,t-2}$	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post Crisis Period	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ATH	-0.001	-0.005***	-0.005***	-0.001	-0.005***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HU_l	-0.001	-0.001	-0.001	-0.001	0.0001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ATH $\times HU_l$	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ATH $\times \Delta ln(RRI_{l,t-12})$	0.03**	0.031**	0.029**	0.029**	0.03**	0.03**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
$HU_l \times \Delta ln(RRI_{l,t-12})$	0.03	0.034	-0.025	-0.033	0.035	-0.036
	(0.069)	(0.069)	(0.069)	(0.077)	(0.069)	(0.077)
ATH$\times HU_l \times \Delta ln(RRI_{l,t-12})$	-0.027	-0.027	-0.028	-0.028	-0.026	-0.026
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Fixed MSA Effect	Y	Y	Y	Y	Y	Y
Fixed Time Effect	Y	Y	Y	Y	Y	Y
F-Stat	8.67	8.74	8.70	8.77	8.71	8.78
R-sq	0.31	0.31	0.31	0.31	0.31	0.31
Observation	1333	1333	1333	1333	1333	1333

Notes:
(a) Median values. MR(1) is the mismatch rate computed by (available but occupied stock / total stock). MR(2) is the mismatch rate computed by (available but occupied stock / vacant stock).
***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.
Constant term is omitted in all models. All interaction terms in real rent equations are insignificant.

Table 15: Panel A: First Difference Models of Long Run Relationships: Mismatch Rate

Independent Variable	**R1**	**R2**	**R5**	**R6**
$\Delta ln(S_{l,t-1})$	-15.864***	-15.873***	-124.111***	-124.133***
	(3.817)	(3.817)	(30.863)	(30.863)
$\Delta ln(RII_{l,t-1})$	-0.222	-0.253	17.166	17.078
	(1.841)	(1.847)	(14.925)	(14.931)
$\Delta ln(EMI_{l,t-1})$	-0.887	-1.026	-23.143	-23.531
	(2.463)	(2.472)	(19.968)	(19.977)
$\Delta ln(POP_{l,t-1})$	34.957#	37.633*	220.128#	227.622#
	(22.792)	(22.875)	(184.822)	(184.901)
Post Crisis Period	0.059	0.049	-0.097	-0.125
	(0.159)	(0.160)	(1.288)	(1.288)
Fixed MSA Effect	Y	Y	Y	Y
Fixed Time Effect	Y	Y	Y	Y
F-Stat	2.05	2.06	1.49	1.49
R-sq	0.09	0.09	0.06	0.06
Observation	1333	1333	1333	1333

Notes:
MR(1) is the mismatch rate computed by (available but occupied stock / total stock). MR(2) is the mismatch rate computed by (available but occupied stock / vacant stock).
***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.
Constant term is omitted in all models.

Table 16: Panel A: First Difference Models of Long Run Relationships: Search Effort Level

Independent Variable	**R1**	**R3**	**R5**
$\Delta ln(RRI_{l,t-1})$	0.023	0.019	0.025
	(0.17)	(0.17)	(0.17)
$\Delta ln(S_{l,t-1})$	-0.493	-0.488	-0.494
	(0.724)	(0.724)	(0.724)
$\Delta ln(RII_{l,t})$	-0.104	-0.094	-0.09
	(0.360)	(0.361)	(0.361)
Post Crisis Period	-0.013	-0.013	-0.013
	(0.025)	(0.025)	(0.025)
Fixed MSA Effect	Y	Y	Y
Fixed Time Effect	Y	Y	Y
F-Stat	3.23	3.23	3.23
R-sq	0.12	0.12	0.12
Observation	1333	1333	1333

Notes:
MR(1) is the mismatch rate computed by (available but occupied stock / total stock). MR(2) is the mismatch rate computed by (available but occupied stock / vacant stock).
***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.
Constant term is omitted in all models.

Table 17: Panel A: Long Run Relationships - Likelihood of Change in Frictional Vacancy with 40% Gross Rental Gap

Independent Variable	**I1a**	**I2a**	**I3a**	**I4a**	**I5a**
Supply Equation(ln($S_{l,t}$))					
$MR_{l,t}$	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GRG40	0.001	0.002	0.001	0.002	0.0003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
GRG40 $\times MR_{l,t}$	-0.0003	-0.0034	-0.0003	-0.0004	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$GRG40_{l,t-4}$	0.039***	0.040***	0.040***	0.041***	0.0401***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$GRG40_{l,t-4} \times MR_{l,t}$	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MSA dummy $\times$ **ln**($RRI_{l,t-12}$)	Y	Y	Y	Y	Y
F-Stat	1.99×10^6	86410	86421	86421	85808
R-sq	0.99	0.99	0.99	0.99	0.99
Mismatch Rate Equation($MR_{l,t}$)					
$GRG40_{l,t}$	-0.269*	-0.253#	-0.269*	-0.2503#	-0.293**
	(0.158)	(0.160)	(0.158)	(0.160)	(0.159)
$GRG40_{l,t-4}$	0.4502***	0.262#	0.446***	0.259#	0.455***
	(0.163)	(0.166)	(0.163)	(0.166)	(0.163)
MSA dummy $\times$ **ln**($S_{l,t-1}$)	N	Y	N	Y	N
F-Stat	32.28	27.62	677.39	531.01	32.00
R-sq	0.64	0.7	0.64	0.7	0.64
Fixed MSA Effect	Y	Y	Y	Y	Y
Fixed Time Effect	Y	Y	Y	Y	Y

Note: Signs ***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 18: Panel A: Robustness Check On Hurricane Effects (Real Rent)

Independent Variable	**H1**	**H2**	**H3**	**H4**
Post Crisis Period	16.085***	16.085***	16.085***	16.085***
	(2.571)	(2.571)	(2.572)	(2.572)
ATH_t	0.008***	0.008***	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
$PORT_l$		6.555		
		(6.499)		
OLD_l			6.555	
			(6.499)	
$TTWD_l$				6.555
				(6.499)
MSA dummy $\times$ **ln**($S_{l,t-1}$)	Y	Y	Y	Y
Fixed MSA Effect	Y	Y	Y	Y
F-Stat	135114	135114	135114	135114
BIC - Simultaneous System	-8053	-8052	-8053	-8053
R-sq	0.79	0.79	0.79	0.79
Observation	1376	1376	1376	1376

Notes: Signs ***, **, * and # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 19: Panel A: Robustness Check on Hurricane Effects (Supply)

Independent Variable	**H1**	**H2**	**H3**	**H4**
Post Crisis Period	omit	omit	4.218***	omit
			(0.117)	
ATH_t	omit	omit	0.039**	0.039**
			(0.02)	(0.02)
HU_l	-1.65***	-1.65***	0.808***	-1.65***
	(0.215)	(0.215)	(0.294)	(0.215)
$ATH_t \times HU_l$	0.016	0.016	0.016	0.016
	(0.048)	(0.048)	(0.048)	(0.048)
$ATH_t \times \mathbf{ln}(RRI_{l,t-12})$	-0.004	-0.004	-0.004	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)
$HU_l \times \mathbf{ln}(RRI_{l,t-12})$	-0.228***	-0.219***	-0.001	-0.228***
	(0.031)	(0.044)	(0.034)	(0.031)
$ATH_t \times HU_l \times \mathbf{ln}(RRI_{l,t-12})$	-0.003	-0.003	-0.003	-0.003
	(0.01)	(0.01)	(0.01)	(0.01)
$PORT_l$		-0.22		
		(0.275)		
$PORT_l \times \mathbf{ln}(RRI_{l,t-12})$		-0.031		
		(0.034)		
OLD_l			-0.22	
			(0.275)	
$OLD_l \times \mathbf{ln}(RRI_{l,t-12})$			-0.11***	
			(0.034)	
$TTWD_l$				0.023
				(0.182)
$TTWD_l \times \mathbf{ln}(RRI_{l,t-12})$				-0.148***
				(0.029)
MSA dummy $\times$ $\mathbf{ln}(RRI_{l,t-11})$	Y	Y	Y	Y
Fixed MSA Effect	Y	Y	Y	Y
Fixed Time Effect	Y	Y	Y	Y
F-Stat	84289	84289	1940000	84289
R-sq	0.99	0.99	0.99	0.99
Observation	1376	1376	1376	1376

Notes: Signs ***, **, * and # represent significant level at 1%, 5%, 10% and 20% respectively.

8 Online Appendix

For panel dataset B, twelve models are compiled. Models B1, B4, B7, and B10 contain a variable of general employment in office using sectors in rent equations. In the models B2, B5, B8, and B11, this variable is replaced by employment in information industries. Population is added to rent equations in other models. Supply elasticity in only 28 MSAs is estimated. Miami and New York are omitted automatically.

Table 20: Im-Pearson-Shin Panel Unit Root Test Results

Variable	**Im-Pearson-Shin W Statistic**		**I(1) (Y/N)**		
	Level	**First Difference**	**1%**	**5%**	**10%**
Panel A: 43 MSAs					
Ln(Real Rent Index) [ln($RRI_{l,t}$)]	0.749	-22.862***	Y	Y	Y
[(a)]Ln(Stock) [ln($S_{l,t}$)]	2.221	-19.667***	Y	Y	Y
[+]Mismatch rate [$MR_{l,t}$]	0.073	-38.662***	Y	Y	Y
[+]Search Effort Level [$SEL_{l,t}$]	3.752	-29.311***	Y	Y	Y
Ln(Real Operating Expense Index) [ln($ROPEXI_{l,t}$)]	-1.141	-27.032***	Y	Y	Y
Ln(Real Personal Income Index) [ln($RII_{l,t}$)]	9.135	-40.125***	Y	Y	Y
[+](Cap - Mortgage Rate) [$CM_{l,t}$]	-0.401	-18.56***	Y	Y	Y
Ln(Employment Index) [ln($EMI_{l,t}$)]	1.948	-11.142***	Y	Y	Y
Ln(Population) [ln($POP_{l,t}$)]	7.972	-13.323***	Y	Y	Y
Panel B: 30 MSAs					
Ln(Real Rent Index) [ln($RRI_{l,t}$)]	0.493	-19.736***	Y	Y	Y
[(a)]Ln(Stock) [ln($S_{l,t}$)]	3.744	-17.997***	Y	Y	Y
[+]Mismatch rate [$MR_{l,t}$]	0.45	-31.78***	Y	Y	Y
[+]Search Effort Level [$SEL_{l,t}$]	3.53	-24.233***	Y	Y	Y
Ln(Real Structure Cost Index) [ln($RSI_{l,t}$)]	-2.841***	-11.574***		I(0)	
Ln(Real Operating Expense Index) [ln($ROPEXI_{l,t}$)]	-1.068	-21.509***	Y	Y	Y
Ln(Real Personal Income Index) [ln($RII_{l,t}$)]	9.13	-34.597***	Y	Y	Y
[+](Cap - Mortgage Rate) [$CM_{l,t}$]	-0.468	-15.321***	Y	Y	Y
Ln(Employment Index) [ln($EMI_{l,t}$)]	1.898	-8.448***	Y	Y	Y
Ln(Employment Index of Information Industry)[ln($INEMI_{l,t}$)]	3.157	-18.188***	Y	Y	Y
Ln(Population) [ln($POP_{l,t}$)]	5.592	-11.97***	Y	Y	Y

Notes: (a) Individual intercept and trend are assumed since the series are non-stationary along trend. Other series assume individual intercept only in the panel unit root test. + Natural logarithm is not taken and original rates (%) are used as input in the model since the series contain zero value. Other variables are transformed in the form of natural logarithm. Signs ***, ** and * represent significant level at 1%, 5% and 10% respectively.

Table 21: Panel Cointegration: Pedroni Test Results

Variables	Panel Statistics				Group Statistics			Cointegrated
	V	Rho	PP	ADF	Rho	PP	ADF	(Y/N)
Panel A (43MSAs):								
RRI equation:								
(Trend) $\ln(RRI_{l,t})$, $\ln(S_{l,t})$, $\ln(EMI_{l,t})$, $\ln(RII_{l,t})$ and $MR_{l,t}$	6.343***	-0.648	-5.16***	-5.402***	0.493	-5.813***	-5.988***	Y
(Trend) $\ln(RRI_{l,t})$, $\ln(S_{l,t})$, $\ln(EMI_{l,t})$ and $\ln(RII_{l,t})$	4.604***	-0.277	-3.214***	-2.11**	0.691	-3.764***	-2.805***	Y
S equation:								
(Trend) $\ln(S_{l,t})$, $\ln(RRI_{l,t})$, $\ln(ROPEXI_{l,t})$, $SEL_{l,t}$, $MR_{l,t}$ and $CM_{l,t}$	11.891***	1.976	-2.377***	-3.474***	3.81	-1.598*	-3.47***	Y
(Trend) $\ln(S_{l,t})$, $\ln(RRI_{l,t})$, $\ln(ROPEXI_{l,t})$, $MR_{l,t}$ and $CM_{l,t}$	6.299***	2.598	-0.609	-1.849**	4.686	0.8	-1.089	N
(Trend) $\ln(S_{l,t})$, $\ln(RRI_{l,t})$, $\ln(ROPEXI_{l,t})$, $SEL_{l,t}$ and $CM_{l,t}$	12.182***	1.166	-2.248**	-3.124***	2.885	-1.536*	-2.952***	Y
(Trend) $\ln(S_{l,t})$, $\ln(RRI_{l,t})$, $\ln(ROPEXI_{l,t})$ and $CM_{l,t}$	3.772***	3.491	1.202	0.583	4.791	1.938	0.503	N
SEL equation:								
(No) $SEL_{l,t}$, $\ln(RRI_{l,t})$, $\ln(S_{l,t})$ and $\ln(RII_{l,t})$	2.494*	-0.6	-1.858*	-2.213**	1.74	-0.485	-1.362*	Y
MR equation:								
(No) $MR_{l,t}$, $\ln(POP_{l,t})$, $\ln(EMI_{l,t})$, $\ln(RII_{l,t})$ and $\ln(S_{l,t})$	1.902	-1.145#	-3.481***	-3.718***	0.544	-4.271***	-5.058***	Y
Panel B (30 MSAs):								
RRI equation:								
(Trend) $\ln(RRI_{l,t})$, $\ln(S_{l,t})$, $\ln(EMI_{l,t})$, $\ln(RII_{l,t})$ and $MR_{l,t}$	2.475***	-2.852***	-7.057***	-6.778***	-1.486*	-6.861***	-6.578***	Y
(Trend) $\ln(RRI_{l,t})$, $\ln(S_{l,t})$, $\ln(EMI_{l,t})$ and $\ln(RII_{l,t})$	3.753***	-4.705***	-7.981***	-7.242***	-3.06***	-7.466***	-6.67***	Y
(Trend) $\ln(RRI_{l,t})$, $\ln(S_{l,t})$, $\ln(INEMI_{l,t})$, $\ln(RII_{l,t})$ and $MR_{l,t}$	5.006***	0.216	-2.741***	-3.892***	1.872	-2.294**	-3.397***	Y
(Trend) $\ln(RRI_{l,t})$, $\ln(S_{l,t})$, $\ln(INEMI_{l,t})$ and $\ln(RII_{l,t})$	5.514***	-0.896#	-3.297***	-3.759***	0.618	-3.25***	-4.107***	Y
(Trend) $\ln(RRI_{l,t})$, $\ln(S_{l,t})$, $\ln(INEMI_{l,t})$, $\ln(RII_{l,t})$, $\ln(POP_{l,t})$ and $MR_{l,t}$	1.755**	-0.08	-4.434***	-4.055***	1.312	-4.367***	-3.539***	Y
(Trend) $\ln(RRI_{l,t})$, $\ln(S_{l,t})$, $\ln(INEMI_{l,t})$, $\ln(RII_{l,t})$ and $\ln(POP_{l,t})$	2.26**	-0.889#	-4.182***	-4.302***	0.669	-3.98***	-4.098***	Y
S equation:								
(Trend) $\ln(S_{l,t})$, $\ln(RRI_{l,t})$, $\ln(RSI_{l,t})$, $\ln(ROPEXI_{l,t})$, $SEL_{l,t}$, $MR_{l,t}$ and $CM_{l,t}$	0.345	4.887	-1.075#	-4.874***	6.792	-1.886**	-5.133***	No Conclusion
(Trend) $\ln(S_{l,t})$, $\ln(RRI_{l,t})$, $\ln(RSI_{l,t})$, $\ln(ROPEXI_{l,t})$, $MR_{l,t}$ and $CM_{l,t}$	0.773	3.281	-1.417*	-4.357***	5.305	-2.07**	-4.989***	Y
(Trend) $\ln(S_{l,t})$, $\ln(RRI_{l,t})$, $\ln(RSI_{l,t})$, $\ln(ROPEXI_{l,t})$, $SEL_{l,t}$ and $CM_{l,t}$	0.461	3.515	-0.973#	-4.054***	5.479	-0.432	-3.548***	N
(Trend) $\ln(S_{l,t})$, $\ln(RRI_{l,t})$, $\ln(RSI_{l,t})$, $\ln(ROPEXI_{l,t})$ and $CM_{l,t}$	0.654	2.68	-0.679	-2.471***	4.587	-0.065	-2.129**	N
SEL equation:								
(No) $SEL_{l,t}$, $\ln(RRI_{l,t})$, $\ln(S_{l,t})$ and $\ln(RII_{l,t})$	2.306*	-0.873	-1.95*	-2.828**	1.189	-0.666	-1.912**	Y
(Trend) $SEL_{l,t}$, $\ln(RRI_{l,t})$, $\ln(S_{l,t})$ and $\ln(RII_{l,t})$	2.671**	-0.277	-2.388**	-4.156***	1.536	-1.455*	-3.701***	Y
MR equation:								
(No) $MR_{l,t}$, $\ln(POP_{l,t})$, $\ln(EMI_{l,t})$, $\ln(RII_{l,t})$ and $\ln(S_{l,t})$	1.271#	-1.174#	-3.723***	-4.855***	0.507	-3.548***	-4.638***	Y
(Trend) $MR_{l,t}$, $\ln(POP_{l,t})$, $\ln(EMI_{l,t})$, $\ln(RII_{l,t})$ and $\ln(S_{l,t})$	0.463	0.378	-2.392***	-2.983***	0.966	-3.354***	-4.032***	Y

Notes: We assume deterministic trend in long run state of RRI and S based on the straightforward law of demand and supply. However, mismatch is caused by landlords' strategy for seeking exceedingly rent opportunities which strongly positively deviate from market level. Furthermore, information released by landlords may not have heterogeneous trend. Thus, we do not assume deterministic trend in MR and SEL for panel dataset A. Signs ***, **, * and # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 22: Panel B: Long Run Relationship of Real Rent ($\ln(RRI_{l,t})$)

Independent Variable	**B1**	**B2**	**B3**	**B4**	**B5**	**B6**	**B7**	**B8**	**B9**	**B10**	**B11**	**B12**
Constant	Omit	Omit	11.855***	Omit	Omit	Omit	Omit	Omit	Omit	Omit	Omit	Omit
			(1.969)									
ln($S_{l,t-1}$)[a]	-2.47	-1.936	-1.029	-2.474	-1.842	-1.064	-2.484	-1.912	-1.114	-2.444	-1.848	-1.14
ln($EMI_{l,t-2}$)	0.409***			0.399***			0.411***			0.402***		
	(0.067)			(0.067)			(0.067)			(0.067)		
ln($INEMI_{l,t-2}$)		0.369***	0.331***		0.365***	0.328***		0.373***	0.336***		0.369***	0.333***
		(0.028)	(0.028)		(0.028)	(0.028)		(0.028)	(0.028)		(0.028)	(0.028)
ln($POP_{l,t-2}$)			-1.165***			-1.151***			-1.153***			-1.142***
			(0.163)			(0.163)			(0.164)			(0.164)
ln($RII_{l,t-4}$)	0.405***	0.684***	1.004***	0.402***	0.676***	0.994***	0.407***	0.687***	1.005***	0.404***	0.68***	0.996***
	(0.081)	(0.043)	(0.062)	(0.081)	(0.043)	(0.061)	(0.081)	(0.043)	(0.062)	(0.081)	(0.043)	(0.062)
$MR_{l,t-1}$	-0.005***	-0.005***	-0.004**	-0.007***	-0.006***	-0.004**	-0.005***	-0.005***	-0.003*	-0.007***	-0.006***	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Post Crisis Period	13.637***	12.397***	Omit	13.959***	12.723***	12.146***	13.525***	12.272***	11.725***	13.824***	12.576***	11.986***
	(2.169)	(2.021)		(2.172)	(2.024)	(1.972)	(2.173)	(2.025)	(1.975)	(2.176)	(2.028)	(1.977)
ATH	0.005*	0.007***	0.007***	0.006*	0.007***	0.007***	0.006*	0.007***	0.007***	0.006*	0.007***	0.007***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MSA dummy × **ln**($S_{l,t-1}$)	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed MSA Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
F-Stat	153193	174961	87.56	153193	174961	182660	153192	174961	182659	153193	174961	182659
BIC - Simultaneous System	-5948	-6059	-6077	-6038	-6144	-6158	-5959	-6073	-6085	-6042	-6152	-6162
R-sq	0.81	0.84	0.85	0.81	0.84	0.85	0.81	0.84	0.85	0.81	0.84	0.85
Observation	990	990	990	990	990	990	990	990	990	990	990	990

Notes: (a) Median values. Signs ***, **, * and # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 23: Panel B: Long Run Relationship of Office Supply ($\ln(S_{l,t})$)

Independent Variable	**B1**	**B2**	**B3**	**B4**	**B5**	**B6**	**B7**	**B8**	**B9**	**B10**	**B11**	**B12**
Constant	Omit	4.158***	4.13***	Omit	4.152***	4.125***	Omit	Omit	Omit	4.139***	4.156***	4.128***
		(0.121)	(0.122)		(0.121)	(0.122)				(0.122)	(0.122)	(0.122)
$\mathbf{ln}(RRI_{l,t-11})^a$	0.125	0.128	0.127	0.124	0.128	0.126	0.122	0.125	0.124	0.121	0.125	0.124
$\mathbf{ln}(RSI_{l,t-11})$	-0.005#	-0.005#	-0.004	-0.006#	-0.005#	-0.005#	-0.007*	-0.006*	-0.005#	-0.007*	-0.006*	-0.006#
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\mathbf{ln}(ROPEXI_{l,t-11})$	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$SEL_{l,t-1}$	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$MR_{l,t-1}$	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$CM_{l,t-2}$	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Post Crisis Period	4.142***	4.158***	Omit	Omit	4.152***	Omit	4.143***	Omit	4.131***	Omit	Omit	Omit
	(0.121)	(0.121)			(0.121)		(0.122)		(0.122)			
ATH_t	0.034	0.033	0.032	4.171***	0.033	4.157***	0.034	4.193***	0.032	4.173***	4.189***	0.032
	(0.027)	(0.027)	(0.027)	(0.12)	(0.027)	(0.12)	(0.027)	(0.12)	(0.027)	(0.12)	(0.12)	(0.027)
HU_l	-0.718***	-0.724***	-0.706***	-0.697***	0.889***	-0.685***	-0.674***	-0.679***	-0.661***	-0.657***	0.933***	-0.645***
	(0.185)	(0.185)	(0.185)	(0.185)	(0.205)	(0.185)	(0.186)	(0.186)	(0.186)	(0.186)	(0.205)	(0.186)
$ATH_t \times HU_l$	-0.048	-0.048	-0.05	-0.048	-0.048	-0.05	-0.047	-0.046	-0.048	-0.046	-0.046	-0.048
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.064)	(0.063)	(0.063)	(0.063)
$ATH_t \times \mathbf{ln}(RRI_{l,t-11})$	-0.008#	-0.008#	-0.008#	-0.008#	-0.008#	-0.008#	-0.008#	-0.008#	-0.008#	-0.008#	-0.008#	-0.008#
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$HU_l \times \mathbf{ln}(RRI_{l,t-11})$	-0.295***	-0.291***	-0.299***	-0.297***	-0.294***	-0.302***	-0.303***	-0.299***	-0.308***	-0.305***	-0.301***	-0.31***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)	(0.035)
$ATH_t \times HU_l \times \mathbf{ln}(RRI_{l,t-11})$	0.011	0.011	0.011	0.011	0.011	0.011	0.01	0.01	0.011	0.01	0.01	0.011
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
$TTWD_l$	0.111	-0.139	-0.117	0.104	0.077	-0.101	0.106	-0.118	0.096	0.099	-0.104	-0.089
	(0.187)	(0.287)	(0.288)	(0.187)	(0.187)	(0.288)	(0.187)	(0.287)	(0.188)	(0.187)	(0.287)	(0.188)
$TTWD_l \times \mathbf{ln}(RRI_{l,t-11})$	-0.192***	-0.19***	-0.201***	-0.193***	-0.191***	-0.202***	-0.193***	-0.19***	-0.201***	-0.193***	-0.191***	-0.201***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.032)	(0.031)	(0.031)	(0.032)
MSA dummy $\times$ $\mathbf{ln}(RRI_{l,t-11})$	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed MSA Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Time Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
F-Stat	1770000	1770000	48465	1770000	1770000	1770000	1770000	1770000	1770000	1770000	1770000	48465
R-sq	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Observation	990	990	990	990	990	990	990	990	990	990	990	990

Notes: (a) Median values. Signs ***, **, * and # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 24: Panel B: Long Run Relationship of Mismatch Rate ($MR_{l,t}$)

Independent Variable	**B1**	**B2**	**B3**	**B4**	**B5**	**B6**	**B7**	**B8**	**B9**	**B10**	**B11**	**B12**
Constant	13.648	13.121	13.879	261.58***	Omit	Omit	Omit	Omit	11.995	Omit	248***	248.234***
	(15.09)	(15.09)	(15.091)	(47.294)					(15.111)		(46.332)	(46.349)
ln($S_{l,t-1}$)	-4.282**	-4.143**	-3.916*	-20.471^a	-18.93^a	-18.272^a	-4.366**	-4.224**	-4.005**	-19.778^a	-18.315^a	-17.929^a
	(2.035)	(2.034)	(2.035)				(2.035)	(2.036)	(2.035)			
ln($RII_{l,t-1}$)	-2.081#	-2.003#	-1.948#	-4.782***	-4.586***	-4.364***	-2.013#	-1.934#	-1.887	-4.79***	-4.592***	-4.389***
	(1.489)	(1.489)	(1.49)	(1.641)	(1.642)	(1.643)	(1.491)	(1.453)	(1.491)	(1.644)	(1.645)	(1.646)
ln($EMI_{l,t-1}$)	-1.872#	-1.835#	-1.819#	1.09	1.187	1.266	-2.099*	-2.07*	-2.059	0.845	0.928	0.999
	(1.213)	(1.213)	(1.213)	(1.539)	(1.539)	(1.54)	(1.215)	(1.215)	(1.215)	(1.542)	(1.542)	(1.543)
ln($POP_{l,t-1}$)	3.329#	3.25#	2.995#	-0.316	0.074	-1.164	3.664*	3.589*	3.36#	-0.335	-0.034	-1.062
	(2.156)	(2.156)	(2.157)	(4.408)	(4.411)	(4.418)	(2.161)	(2.161)	(2.161)	(4.415)	(4.442)	(4.425)
Post Crisis Period	Omit	Omit	Omit	Omit	249.827***	250.597***	11.905	11.367	Omit	259.35***	Omit	Omit
					(46.201)	(46.218)	(15.109)	(15.11)		(46.309)		
MSA dummy $\times$ ln($S_{l,t-1}$)	N	N	N	Y	Y	Y	N	N	N	Y	Y	Y
Fixed MSA Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Time Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
F-Stat	26.44	26.45	26.51	27.54	610.16	610.14	665.13	665.14	26.52	610.15	27.49	27.47
R-sq	0.63	0.63	0.64	0.72	0.72	0.72	0.63	0.64	0.64	0.72	0.72	0.72
Observation	990	990	990	990	990	990	990	990	990	990	990	990

Notes:
(a) Median values across 30 MSAs.
(b) Signs ***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 25: Panel B: Long Run Relationship of Search Effort Level ($SEL_{l,t}$)

Independent Variable	**B1**	**B2**	**B3**	**B4**	**B5**	**B6**	**B7**	**B8**	**B9**	**B10**	**B11**	**B12**
Constant	Omit	15.797***	15.794***	Omit	Omit	Omit	Omit	2.688	3.154	Omit	0.523	1.013
		(2.104)	(2.104)					(12.858)	(12.857)		(12.859)	(12.859)
ln($RRI_{l,t-1}$)	-0.626***	-0.628***	-0.646***	-0.642***	-0.643***	-0.662***	0.7^a	0.758^a	0.772^a	0.697^a	0.757^a	0.771^a
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)						
ln($S_{l,t-1}$)	-4.041***	-4.01***	-3.984***	-4.041***	-4.012***	-3.986***	-3.234^a	-3.266^a	-3.344^a	-3.224^a	-3.26^a	-3.317^a
	(0.421)	(0.421)	(0.421)	(0.421)	(0.421)	(0.421)						
ln($RII_{l,t}$)	1.498***	1.514***	1.505***	1.515***	1.531***	1.523***	1.631***	1.623***	1.627***	1.642***	1.632***	1.635***
	(0.262)	(0.262)	(0.262)	(0.262)	(0.262)	(0.262)	(0.311)	(0.311)	(0.311)	(0.311)	(0.311)	(0.311)
Post Crisis Period	16.015***	Omit***	Omit	16.014***	15.8***	15.797***	3.613	Omit	Omit	1.341	Omit	Omit
	(2.104)			(2.104)	(2.104)	(2.104)	(12.863)			(12.863)		
MSA dummy $\times$ **ln**($S_{l,t-1}$)	N	N	N	N	N	N	Y	Y	Y	Y	Y	Y
MSA dummy $\times$ **ln**($RRI_{l,t-1}$)	N	N	N	N	N	N	Y	Y	Y	Y	Y	Y
Fixed MSA Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Time Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
F-Stat	64.22	133.83	63.66	134.16	133.85	133.61	113.05	55.52	55.59	113.04	55.51	55.58
R-sq	0.8	0.8	0.8	0.8	0.8	0.8	0.87	0.87	0.87	0.87	0.87	0.87
Observation	990	990	990	990	990	990	990	990	990	990	990	990

Notes:
(a) Median values across 30 MSAs.
(b) Signs ***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 26: Panel B: Short Run Relationship of Real Rent ($\Delta ln(RRI_{l,t})$)

Independent Variable	**B1**	**B2**	**B3**	**B10**	**B11**	**B12**
$\Delta ln(S_{l,t-1})$	-0.16	-0.378**	-0.389**	-0.155	-0.372**	-0.381**
	(0.159)	(0.159)	(0.165)	(0.159)	(0.159)	(0.165)
$\Delta ln(EMI_{l,t-2})$	0.53***			0.527***		
	(0.065)			(0.065)		
$\Delta ln(INEMI_{l,t-2})$		0.238***	0.242***		0.238***	0.241***
		(0.035)	(0.050)		(0.034)	(0.035)
$\Delta ln(POP_{l,t-2})$			0.277			0.266
			(0.395)			(0.395)
$\Delta ln(RII_{l,t-4})$	0.203***	0.278***	0.307***	0.203***	0.277***	0.306***
	(0.041)	(0.041)	(0.042)	(0.041)	(0.041)	(0.042)
$\Delta MR_{l,t-1}$	-0.002#	-0.003**	-0.003**	-0.002*	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$ECT^{RRI}_{l,t-1}$	-0.145***	-0.171***	-0.16***	-0.148***	-0.174***	-0.163***
	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.016)
Constant	-0.003***	-0.001	-0.002#	-0.003	-0.001	-0.002#
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
F-Stat	61.65	54.59	41.11	62.53	55.61	41.97
Bayesian Information Criterion	-12705	-12680	-12655	-12734	-12707	-12681
R-sq	0.23	0.21	0.19	0.23	0.21	0.19
Observation	960	960	960	960	960	960

Notes: Bayesian Information Criterion measures suitability of the entire simultaneous system. Signs ***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 27: Panel B: Short Run Relationship of Office Stock ($\Delta ln(S_{l,t})$)

Independent Variable	M1	M2	M3	M10	M11	M12
Constant	0.003***	0.003***	0.002***	0.003***	0.003***	0.003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\Delta ln(RRI_{l,t-11})$	0.021***	0.021***	0.021***	0.02***	0.021***	0.021***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$\Delta ln(RSI_{l,t-11})$	-0.001	-0.002	-0.002	-0.001	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$\Delta ln(ROPEXI_{l,t-11})$	0.005**	0.005**	0.005**	0.005**	0.005*	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\Delta SEL_{l,t-1}$	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta MR_{l,t-1}$	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$\Delta CM_{l,t-2}$	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
$ECT^S_{l,t-1}$	-0.073***	-0.074***	-0.074***	-0.072***	-0.073***	-0.073***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
F-Stat	9.36	9.57	9.65	9.15	9.36	9.42
R-sq	0.07	0.07	0.07	0.07	0.07	0.07
Observation	960	960	960	960	960	960

Note: Signs ***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 28: Panel B: Short Run Relationship of Mismatch Rate ($\Delta MR_{l,t}$)

Independent Variable	**M1**	**M2**	**M3**	**M10**	**M11**	**M12**
Constant	0.069**	0.07**	0.069**	.075**	0.075***	0.075**
	(0.029)	(0.029)	(0.03)	(0.029)	(0.029)	(0.029)
$\Delta ln(S_{l,t-1})$	-3.58	-3.713	-3.721	-4.575	-4.736	-4.722
	(4.087)	(4.086)	(4.086)	(4.065)	(4.063)	(4.063)
$\Delta ln(RII_{l,t-1})$	1.661#	1.655#	-1.643#	1.646#	1.644#	1.638#
	(1.055)	(1.055)	(1.055)	(1.05)	(1.049)	(1.049)
$\Delta ln(EMI_{l,t-1})$	-8.852***	-9.103***	-9.074***	-8.439***	-8.629***	-8.554***
	(1.64)	(1.639)	(1.639)	(1.632)	(1.631)	(1.631)
$\Delta ln(POP_{l,t})$	8.553	8.666	8.991	7.174	7.212	7.517
	(9.545)	(9.544)	(9.556)	(9.501)	(9.497)	(9.51)
$ECT^{MR}_{l,t-1}$	-0.215***	-0.215***	-0.215***	-0.258***	-0.26***	-0.26***
	(0.02)	(0.02)	(0.02)	(0.023)	(0.023)	(0.023)
F-Stat	27.91	28.43	28.49	30.34	31.03	31.06
R-sq	0.13	0.13	0.13	0.13	0.13	0.13
Observation	960	960	960	960	960	960

Note: Signs ***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 29: Panel B: Short Run Relationship of Search Effort Level ($\Delta SEL_{l,t}$)

Independent Variable	**M1**	**M2**	**M3**	**M10**	**M11**	**M12**
Constant	0.026***	0.026***	0.026***	0.026***	0.026***	0.026***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\Delta ln(RRI_{l,t-1})$	0.078	0.091	0.093	0.089	0.111	0.11
	(0.148)	(0.148)	(0.148)	(0.146)	(0.146)	(0.146)
$\Delta ln(S_{l,t-1})$	-2.671***	-2.679***	-2.678***	-2.688***	-2.706***	-2.722***
	(0.823)	(0.823)	(0.823)	(0.815)	(0.816)	(0.816)
$\Delta ln(RII_{l,t})$	0.463**	0.467**	0.467**	0.491**	0.505**	0.504**
	(0.206)	(0.206)	(0.206)	(0.204)	(0.204)	(0.204)
$ECT^{SEL}_{l,t-1}$	-0.178***	-0.158***	-0.18***	-0.244***	-0.243***	-0.242***
	(0.02)	(0.02)	(0.02)	(0.024)	(0.024)	(0.024)
F-Stat	24.09	24.2	24.51	29.81	29.41	29.36
R-sq	0.1	0.1	0.1	0.11	0.11	0.11
Observation	960	960	960	960	960	960

Note: Signs ***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.

Table 30: Panel B: First Difference Models of Long Run Relationships: Real Rent

Independent Variable	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**
$\Delta ln(S_{l,t-1})^a$	0.307	0.308	0.291	0.291	0.329	0.323
$\Delta ln(EMI_{l,t-2})$	0.672***	0.673***	0.683***	0.684***	0.684***	0.684***
	(0.069)	(0.069)	(0.068)	(0.068)	(0.068)	(0.068)
$\Delta ln(RII_{l,t-4})$	0.209***	0.209***	0.21***	0.21***	0.21***	0.211***
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
$\Delta MR(1)_{l,t-1}$	-0.002	-0.001				
	(0.001)	(0.001)				
$\Delta MR(2)_{l,t-1}$					0.0003#	0.0003#
					(0.0002)	(0.0002)
Post Crisis Period	-0.009**	-0.009**	-0.009**	-0.009**	-0.01**	-0.01**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ATH	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fixed MSA Effect	Y	Y	Y	Y	Y	Y
F-Stat	4.14	4.15	4.18	4.19	4.15	4.16
BIC - Simultaneous System	-10709	-9831	-12714	-11838	-6802	-5926
R-sq	0.21	0.21	0.21	0.21	0.21	0.21
Observation	960	960	960	960	960	960

Notes:
(a) Median values. MR(1) is the mismatch rate computed by (available but occupied stock / total stock). MR(2) is the mismatch rate computed by (available but occupied stock / vacant stock).
***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.
Constant term is omitted in all models.
All interaction terms in real rent equations are insignificant.

Table 31: Panel B: First Difference Models of Long Run Relationships: Office Stock

Independent Variable	R1	R2	R3	R4	R5	R6
$\Delta ln(RRI_{l,t-11})^a$	0.009	0.01	-0.002	0.003	0.005	0.015
$\Delta ln(RSI_{l,t-11})$	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\Delta ln(ROPEXI_{l,t-11})$	0.005**	0.005**	0.004**	0.005**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\Delta SEL_{l,t-1}$	-0.00002		0.0001		0.0001	
	(0.001)		(0.001)		(0.001)	
$\Delta MR(1)_{l,t-1}$	-0.001**	-0.001**				
	(0.0002)	(0.0002)				
$\Delta MR(2)_{l,t-1}$					-0.0001**	-0.0001***
					(0.00003)	(0.00003)
$\Delta CM_{l,t-2}$	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post Crisis Period	0.006***	0.006***	0.005***	0.005***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ATH	-0.005***	-0.005***	-0.004***	-0.003*	-0.003*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
HU_l	-0.000	-0.0001	0.003***	0.003***	0.0003	0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ATH $\times HU_l$	0.0004	0.0004	0.0003	0.0003	0.0004	0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ATH $\times \Delta ln(RRI_{l,t-11})$	0.030**	0.005	0.007	0.008	0.003	0.005*
	(0.014)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)
$HU_l \times \Delta ln(RRI_{l,t-11})$	-0.053	-0.054	0.104*	0.102*	0.101*	-0.052
	(0.053)	(0.053)	(0.059)	(0.058)	(0.059)	(0.053)
ATH$\times HU_l \times \Delta ln(RRI_{l,t-11})$	-0.009	-0.009	-0.012	-0.011	-0.009	-0.009
	(0.029)	(0.029)	(0.03)	(0.03)	(0.029)	(0.029)
$TTWD_l$	-0.001	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$TTWD_l \times \Delta ln(RRI_{l,t-11})$	0.008	0.008	0.011	-0.243	-0.027	-0.025
	(0.044)	(0.044)	(0.044)	(0.05)	(0.049)	(0.049)
Fixed MSA Effect	Y	Y	Y	Y	Y	Y
Fixed Time Effect	Y	Y	Y	Y	Y	Y
F-Stat	10.77	10.87	10.76	10.86	10.73	10.83
R-sq	0.35	0.35	0.35	0.35	0.35	0.35
Observation	960	960	960	960	960	960

Notes: (a) Median values. MR(1) is the mismatch rate computed by (available but occupied stock / total stock). MR(2) is the mismatch rate computed by (available but occupied stock / vacant stock). ***, **, * and # represent significant level at 1%, 5%, 10% and 20% respectively. The constant term is omitted in all models. All interaction terms in real rent equations are insignificant.

Table 32: Panel B: First Difference Models of Long Run Relationships: Mismatch Rate

Independent Variable	**R1**	**R2**	**R5**	**R6**
$\Delta ln(S_{l,t-1})^{a}$	-16.085	-16.097	-113.262	-113.299
$\Delta ln(RII_{l,t-1})$	0.595	-0.583	22.29#	22.316#
	(1.922)	(1.924)	(14.701)	(14.702)
$\Delta ln(EMI_{l,t-1})$	-2.423	-2.377	-19.478	-19.553
	(2.832)	(2.835)	(21.665)	(21.667)
$\Delta ln(POP_{l,t-1})$	63.793**	63.031**	480.555**	482.073**
	(26.375)	(26.4)	(201.746)	(186.851)
Post Crisis Period	-0.073	-0.07	-0.372	-1.583
	(0.173)	(0.173)	(1.293)	(1.32)
Fixed MSA Effect	Y	Y	Y	Y
Fixed Time Effect	Y	Y	Y	Y
F-Stat	1.82	1.81	1.33	1.33
R-sq	0.14	0.14	0.1	0.1
Observation	960	960	960	960

Notes:
(a) Median values. MR(1) is the mismatch rate computed by (available but occupied stock / total stock). MR(2) is the mismatch rate computed by (available but occupied stock / vacant stock).
***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.
Constant term is omitted in all models.

Table 33: Panel B: First Difference Models of Long Run Relationships: Search Effort Level

Independent Variable	**R1**	**R3**	**R5**
$\Delta ln(RRI_{l,t-1})^a$	0.058	0.07	0.068
$\Delta ln(S_{l,t-1})^a$	0.724	0.749	0.76
$\Delta ln(RII_{l,t})$	-0.117	-0.113	-0.118
	(0.393)	(0.394)	(0.394)
Post Crisis Period	-0.057**	-0.058**	-0.058**
	(0.028)	(0.028)	(0.028)
Fixed MSA Effect	Y	Y	Y
Fixed Time Effect	Y	Y	Y
F-Stat	2.34	2.34	2.34
R-sq	0.2	0.2	0.2
Observation	960	960	960

Notes:
(a) Median values. MR(1) is the mismatch rate computed by (available but occupied stock / total stock). MR(2) is the mismatch rate computed by (available but occupied stock / vacant stock).
***, ** and * as well as # represent significant level at 1%, 5%, 10% and 20% respectively.
Constant term is omitted in all models.