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AGGLOMERATION EFFECTS AND LIQUIDITY GRADIENTS IN LOCAL RENTAL HOUSING MARKETS

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Agglomeration Effects and Liquidity Gradients in Local Rental Housing Markets*

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Abstract

This paper analyzes empirically the relation between liquidity in rental housing markets and urban agglomeration effects. Online market platforms resemble a limit order book, where landlords provide and potential tenants remove liquidity. Using listed rent offers, I compute several liquidity measures and study their variation across local rental markets. Local liquidity is negatively related to the distance to nearby located agglomeration centers, manifesting in a decreasing liquidity gradient. I show that more distant local rental markets are exposed to a higher systematic illiquidity risk. Furthermore, more thinly traded rental markets offer lower capitalization rates for investors.

JEL Classification: $G12$, $R31$, $R40$
Key words: Urban agglomeration; Housing market; Limit Order Book; Liquidity.

1 Introduction

Does liquidity in rental housing markets depend on urban agglomeration externalities? Do local rental markets with a greater distance from agglomeration centers suffer from a systematically higher illiquidity? Positive externalities to nearby located rental markets may arise from labor market conditions in the urban agglomeration center. Eeckhout, Pinheiro, and Schmidheiny (2014), for instance, show how the productivity of highly skilled employees and of less skilled workers in the service sector reinforces each other in urban centers. A more productive labor market attracts a large share of qualified human capital and specialized labor force (see, e.g., Glaeser and Gottlieb (2009)). Households focus their search effort on the geographic location nearby their workplace (Piazessi, Schneider, and Stroebel (2014)). As a consequence, the location choice of households depends on the distance to the local agglomeration center, and, therefore, has an impact on the local housing market liquidity.

This paper analyzes the impact of urban agglomerations on the liquidity of local rental housing markets. The economic environment after the 2007/08 financial crisis is characterized by an income growth below house price inflation, stricter bank lending requirements, and high user costs of home ownership. Hence, with home ownership being less attractive, the rental housing market becomes more important.[1] I empirically test how the proximity to nearby located urban agglomeration centers affects liquidity in local rental markets. Property transactions and rent agreements involve large search and matching costs for the market participants. Because of these search frictions, the (rental) price and the individual liquidity of heterogeneous housing units are jointly determined as the equilibrium outcome. However, to the best of my knowledge, there is no literature about liquidity in the rental housing market and its market-specific driving fundamentals.

In housing markets, liquidity is defined as the individual time on the market, i.e.,

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[1]For instance, the percentage share of households in the U.S. who rent housing instead of owning increased from 31% in 2005 to 37% in 2015 (Joint Center For Housing Studies of Harvard University (2015)).

the time until an offered property is sold (e.g., Han and Strange (2015)). However, this concept captures liquidity only from the perspective of the property-owner. Compared to stock markets, the online trading platform for rental housing markets can be compared to a limit order book. Limit orders that cannot be immediately executed at the specified price are placed in the limit order book until a trading counterparty is willing to accept the order or the investors removes it from the order book. The resemblance to limit order markets has important implications for the market participants with respect to liquidity demand and supply (see, e.g., Foucault, Kadan, and Kandel (2005), Bloomfield, O'Hara, and Saar (2005), Putnins and Michayluk (2015)). Landlords are liquidity suppliers who are exposed to the waiting time when their released offer cannot be executed. Potential tenants demand liquidity. They remove liquidity from the online platform and compete for available offers of heterogeneous, unique rental units. Landlords are exposed to liquidity demand, since a higher time on the market, or the non-execution risk, reflects in a higher opportunity cost of not realized rental cash flows. From the perspective of the potential tenant, the crucial aspect of liquidity is the availability of rental offers, i.e., liquidity provided by landlords.

I focus on the rental housing market in Switzerland. The Swiss housing market provides an ideal testing ground to understand systematic differences across local rental market liquidity. First, homeownership rates in Switzerland are among the lowest compared to international levels.[2] The high rate of realized tenancies provides an extensive dataset to learn about the liquidity in thinly traded rental housing markets. For instance, the market for apartments in Switzerland increased from 3.5 Mio apartments in total in 2000 to nearly 4.3 Mio in 2014, with 60% of them rented out by private or institutional property owners or investors.[3] Second, the average age of homeowners in Switzerland between 2000 and 2016 was around 54 to 57. Among 35-year old individuals, only 22%

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[2]With 44.5% in 2014, the homeownership rate in Switzerland is lower than in e.g., Germany (52.5%), the United States (64.5%), France (65%), or Spain (78.8%). The data is obtained from Eurostat (Data Explorer-Distribution of population by tenure status, type of household and income group) and the Federal Reserve Economic Data (FRED), Federal Reserve Bank of St. Louis.

[3]The figures are from the Swiss Federal Office of Housing (BWO).

own a house. Switzerland also has a high immigration rate, with 94% of immigrants renting apartments in the first years.[4] The location choice of these highly skilled household groups is affected by the attractiveness of nearby located agglomeration centers. Third, I exploit the limited amount of large agglomeration centers in Switzerland in my research design. The emergence of concentrated commuting areas due to the country-specific topography allows me to study how rental market liquidity is related to local agglomeration externalities.

I use listed rent offers that are collected from Swiss online real estate trading platforms. The adverts include information about hedonic characteristics, the release date, as well as the end date, when they are removed from the online platform. The sample ranges from 2004 to 2015. I compute several liquidity proxies for local rental housing markets. Each measure covers a different liquidity dimension, such as the transaction volume, the market inventory, and the time on the market. I compare the economic intuition of the liquidity measures and discuss their implications for the market participants.

I provide a systematic analysis of the cross-sectional variation among local market liquidity. In a first step, I find empirical evidence of a decreasing liquidity gradient, defined as a negative relation between the geographic distance to the nearby located urban agglomeration center and the corresponding local market liquidity. The main challenge is to disentangle the agglomeration effect from local market characteristics that are jointly correlated with liquidity and geographic distance. For instance, potential tenants consider the affordability, i.e., the rental price, in their location choice. Several papers, such as Krainer (2001), Genesove and Han (2012), Head, Lloyd-Ellis, and Sun (2014), find a negative correlation between the property-specific transaction price and the time on the market in the owner-occupied housing market. I carefully disentangle these variables from each other to mitigate potential concerns about spurious correlation between liquidity and distance to the agglomeration center that might emerge from the affordability in rental

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[4]The figures are provided by a report from Credit Suisse (2016).

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markets. In my identification strategy, I control for market-specific fundamentals that influence the location choice of households. The remaining systematic difference across liquidity can then be related to the distance to the local agglomeration center.

In a second step, I analyze the exposure of local liquidity to urban agglomeration externalities. The identification is based on the interaction of the geographic distance to the urban agglomeration center with the economic performance of the center over time. Thereby, I isolate the impact of agglomeration externalities on nearby located rental market liquidity. As a proxy for the attractiveness of urban labor markets, I use the Credit Swiss Site Quality Index. This index ranks the agglomeration centers according to their competitiveness to attract firms and qualified labor force, their investments in infrastructure, tax incentives, and the connectivity to regional airports. I show that positive agglomeration externalities on local market liquidity are attenuating with increasing distance between the rental market and its urban center. I also show that an increase in the attractiveness of the agglomeration center is related to a higher systematic liquidity risk for the landlord and potential liquidity dry-outs in more distant local rental markets.

Furthermore, I focus on the economic implications of systematic illiquidity from the perspective of investors, who buy rental units to rent them out. I show that more thinly traded, illiquid markets provide lower capitalization rates. Investors earn a lower income from the rental cash flow on their investment. My findings suggest that this is related to a rental price discount offered by landlords as an incentive for potential tenants to locate in less attractive rental housing markets.

This paper provides new insights into the liquidity in thinly traded real estate markets. Empirical studies focus on search and matching costs (Williams (2014), Piazessi, Schneider, and Stroebel (2014)), and how these trading frictions are related to the individual, property-specific illiquidity, as measured by the time on the market before finding a trading counterparty (e.g., Krainer (2001), Genesove and Han (2012)). I focus on the systematic component of market-specific liquidity and the implications for the partici-

pants. For instance, a systematic lower local market liquidity exposes landlords to a higher non-execution risk.

Compared to the previous literature on real estate, I focus on liquidity in the rental housing markets. This market differs from the one of owner-occupied housing. The concept of liquidity and its implications for the market participants are different in both markets. For instance, the decision of a homeowner to move to a new location depends on the time it takes to sell his house (Head and Lloyd-Ellis (2012)). However, in the rental market, the time to find a new tenant matters only for the landlord. Tenants can terminate their rent contract. Furthermore, the location choice of individuals, and therefore the implied local liquidity demand, is directly linked to the local labor market condition of the agglomeration center. While property purchases are debt-financed with mortgages using the underlying property value as collateral, rent payments to the landlord are financed through the labor income of the household.

I also highlight the role of urban economic aspects in the determination of the housing market equilibrium. Referring to the theoretical work of Alonso (1964), Mills (1969), and Muth (1969), the rent gradient hypothesis states that the rent level is negatively related to the commuting costs to the urban center. The location choice of households follows the compensation principle under the spatial equilibrium, implying that households are indifferent between locations as long as higher commuting costs to the agglomeration center are compensated by lower rents. This paper contributes to the empirical literature on the relation between commuting costs and rent gradients (Zheng and Kahn (2008), McMillen (2015)), wage levels (Mulalic, Ommeren, and Pilegaard (2014)), and population densities (Ahlfeldt, Redding, Sturm, and Wolf (2015)) and shifts the focus to market liquidity.

The better understanding of local liquidity, and its driving fundamentals, has also important implications for the participants in the rental market and provides a guidance for targeted government interventions. The housing tenure choice depends on individ-

ual preferences, wealth considerations, and the living horizon in a specific location (see, e.g., Sinai and Souleles (2005)). Particularly, the location choice of potential tenants is relevant for landlords. The rental cash flow contributes to their wealth and provides an additional income source of their private old-age provision. From a policy perspective, my findings suggest the need of specific investments in local infrastructure and improvements in commuting times to the urban center (see, e.g., Brinkman (2016)). These investments promote liquidity in less attractive local markets and should be preferred to direct corrections in the rental market, such as rent controls as an instrument to dampen the excess housing demand in attractive municipalities.

The paper is structured as follows: Section 2 derives a set of testable economic predictions. Section 3 presents the data. Section 4 discusses the identification strategy. Section 5 shows the empirical results. Section 6 concludes.

2 Local Liquidity in Rental Housing Markets

In this section, I focus on the economic implications of online real estate platforms and how the interaction between local landlords and tenants determines the market liquidity. I then derive several empirically testable hypotheses about the relation between local rental market liquidity and urban agglomeration externalities.

Market Structure: Housing markets are geographically segmented. Online real estate portals channel the asymmetric information between the participants in segmented rental markets to centralized marketplaces. These platforms facilitate a more efficient search and matching process. Comparing the rental housing market platform to stock markets, online trading portals resemble a limit order book. In the rental housing market, property owners release the rent offers on the online platform. Potential tenants can screen the listed entries and search for the optimal offer. The self-selection of potential tenants to their preferred location and listings reduces the search costs of property owners. They

shift the search incentives to their trading counterparties, who are better informed about their individual preferences (Williams (2014)). As a consequence, the landlord is exposed to the time on the market for the rent offer to be executed. The waiting time reflects the opportunity cost of not realized rental income until a potential tenant agrees to sign the contract for the rental unit at the offered rental price and location. Following the argumentation of Foucault, Kadan, and Kandel (2005), the landlord acts as a liquidity provider in online rental housing platforms. Tenants demand liquidity and remove it from the market with realized rent agreements. Regarding liquidity, they are concerned about the availability, i.e., liquidity supply, of vacant rental space. This argumentation is in line with recent studies, such as Bloomfield, O'Hara, and Saar (2005), Putnins and Michayluk (2015), who argue that in limit order books the better informed market participants acts as a liquidity provider. In housing markets, landlords are better informed about hedonic characteristics of their rental units, while they are unfamiliar with the individual preferences of their counterparty. By releasing rent offers, landlords signal the availability of their rental unit.

Testable Hypotheses: In the following, I present several hypotheses about liquidity in the rental market that I empirically test. For each hypothesis, I discuss the underlying economic intuition.

The first hypothesis derives from the location choice of individual households. Costa and Kahn (2000), Compton and Pollak (2007), for instance, link the location choice, particularly of highly skilled individuals with human capital, to the labor market in agglomeration centers. The business environment in agglomeration centers attracts companies and employers to settle near them. For illustration, consider the local labor market in the urban agglomeration center that is attractive for individual households. This increases the implied demand in the corresponding local rental market, given the supply of vacant space. From perspective of the landlord, this market is highly liquid. Competition among potential tenants for available rental units leads to a low time on the market. Because of

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the competition among potential tenants, individuals with the highest willingness to pay locate closer to the agglomeration center, while individuals with a lower rental reservation price are forced to locate to rental markets with a greater distance. A local rental market in a more rural area might be characterized by a low demand. Landlords are confronted with a systematic illiquidity, in terms of a high time on the market, that reflects a high opportunity cost of sacrificed rental cash flow. From the perspective of the tenant, the limited amount of rent offers, i.e., the availability, in combination with competition among remaining households for vacant rental space, makes rural, more distant rental markets more illiquid, while the trading activity and therefore the turnover rate among tenants is higher in the agglomeration center.

Hypothesis 1: *The negative liquidity gradient indicates that market liquidity decreases with increasing geographic distance of the local rental market from the urban agglomeration center.*

Agglomeration externalities increase the attractiveness of urban centers because of a higher productivity and corresponding wage levels. Benefits from the urban labor market are accompanied with a better infrastructure and superior local amenities, such as a more diverse cultural variety or better schooling. Chen and Rosenthal (2008) show that agglomeration externalities affect the mobility decision of individual households, and therefore, on the implied local liquidity. The externality effect is largest on its own rental housing market and decreases with increasing distance. The agglomeration center absorbs liquidity from nearby located local rental housing markets. Over time, more distant rental markets are confronted with a systematic higher illiquidity risk that might lead to a potential liquidity dry-out.

Hypothesis 2: *The impact of agglomeration externalities in urban centers on local rental markets attenuates with increasing geographic distance between both locations. More distant rental markets are exposed to a systematic higher illiquidity risk over time.*

Systematic illiquidity, measured as a higher expected time on the market of the

listed rental offers, exposes the landlord to the opportunity cost of not realized rental cash flows. To attract potential tenants, they offer a market-specific rental price discount on their individual offered rental unit. From the perspective of a potential investor, who buys properties to rent them out, the illiquidity discount drives down the expected cash flow that can be obtained from investments in the rental market. More specifically, the capitalization rate, defined as current income that can be obtained per currency unit of invested property value, is lower in systematically less liquid local markets.

Hypothesis 3: *Illiquidity discounts in rental housing markets lead to lower rental prices in systematically more illiquid, thinly traded local markets. Potential property investors can earn a lower current income component from the rental cash flow stream of the invested property.*

3   Data Description

The dataset consists of listed rental offer adverts in Switzerland. All entries are collected from several online real estate market platforms, such as *Immoscout24*. The sample covers a total of 2,183,944 rental offers in 2,746 local markets from January 2004 to December 2015. Each municipality is defined as a local market.[5] The listed entries include the posted rental offers and information about hedonic characteristics and locational amenities of the rental unit.[6] Based on the release and the exit date of each entry, I compute the individual duration, or time on the market of the rental unit. The property-specific time on the market serves as an individual liquidity measure. The average duration on the market equals 53 days. The minimum time to find a tenant contains 1 trading day. I censor the duration at a maximum of 1000 trading days to exclude potential outliers. Figure 1

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[5]Local markets are disaggregated at the BFS-code level. The Swiss Federal Statistical Office uses the BFS code numbers up to four digits to uniquely assign each municipality in Switzerland. In 2016, Switzerland consists of 2295 municipalities. For illustration, the city Zurich is defined as one local market.

[6]Section A of the Internet Appendix provides a discussion of the different hedonic attributes. I use the hedonic characteristics to construct market-specific rental price indices. Table D.1 in the Appendix shows the sensitivity of the rental price offers to the individual characteristics of the rental unit.

provides an overview of the survival rate of the listings in the online search platforms. The nonparametric Kaplan-Meier estimate of the survival function indicates the proportion of individual offers that are still listed on the online platform after a specific number of trading days. The function is monotonically decreasing to zero. For instance, only around 25% of the listed offers are available on the market after 50 trading days.

[INSERT FIGURE 1 HERE]

Table 1 provides a descriptive summary of the time on the market, the rental price offer, and the corresponding hedonic attributes for the cross-sectional listings. The average offered rent equals CHF 1665.97. I use listed rent offers as a proxy for the realized rental price. As a limitation of the dataset, rental price adjustments of released offers cannot be observed. This raises a potential upward bias in using offer prices as a proxy, since landlords tend to lower their released rent offer the longer the property is available on the market. These concerns can be mitigated by the following argumentation: First, I follow Genesove and Mayer (2001) in interpreting the offered price as the seller-revealed reservation price. Second, the underlying rental value is not determined by the bargaining power of the property owner and the tenant, as this is the case in the owner-occupied housing market, where buyers and sellers trade about the transaction price. The tenancy law in Switzerland allows rental price adjustments, but for established rent agreements, rent control allows adjustments to be only within a range around a reference mortgage rate. To keep their listings attractive for potential tenants, landlords most likely release rent offers that do not deviate too much from this reference value conditional on the housing characteristics. For some listings, the rental price is proprietary and cannot be screened by potential tenants. The average living surface covers 84.74 square meters and the average number of rooms is equal to 3.35.[7] The listings also include dummy variables to capture the hedonic characteristics of apartments.

[INSERT TABLE 1 HERE]

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[7]The number of rooms exclude the kitchen and bathrooms of the rental units.

I provide the cross-sectional distribution of liquidity supply from landlords. Figure 2 shows the cross-sectional distribution of the released rent offers from 2004 to 2015. For each municipality, the number of observed listed offers is ranked from low (less than 10) to high (more than 1600). The number of released rent offers is largest in municipalities within the commuting area of local urban agglomeration centers. The liquidity supply is lower in more distant rural municipalities. As agglomeration centers, I use the five largest cities in Switzerland, Zurich, Geneva, Basel, Lausanne, and Bern. In 2015, the population ranges from 396,027 in Zurich to 130,015 in Bern. To analyze the impact of urban agglomeration externalities on the liquidity level in the rental housing market, I focus exclusively on local municipalities that are included in the commuting area of these five largest cities in Switzerland. For this, I follow the definition of the Federal Statistical Office and only consider municipalities that belong to the local labor market region of the local agglomeration centers.[8]

[INSERT FIGURE 2 HERE]

3.1   Local Liquidity Measures

This section discusses the liquidity measures for local rental housing markets. Each variable focuses on a different dimension of liquidity, such as the transaction volume, the inventory level, and the time on the market of the listed rent offer. I carefully differentiate between liquidity supply, provided by the landlord, and local market liquidity. Liquidity supply, or the availability of rental units, is the most relevant aspect from the perspective of a potential tenant. However, I focus on local liquidity that also considers the demand-side from tenants, whose location choice depends on potential agglomeration externalities. Conceptually, my liquidity measures are defined conditional on liquidity

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[8]For illustration, Figure D.1 in the Internet Appendix provides an overview of the municipalities that are included in the further empirical analysis. The colored surface indicates the municipalities that belong to the labor market region of one of the five agglomeration centers. I select only these local markets in the dataset for the further empirical analysis. The definition of a labor market region follows that of the Federal Statistical Office.

supply, since all proxies are based on released rent offers. Local liquidity is calculated at an annual level.

Transaction Volume: As a first proxy, I compute the transaction volume for each municipality i and each time period t. This measure is defined as the sum over all new generated monthly cash flows based on realized rent agreements for apartments that are removed from the online market platform, divided by the total number of realized rent agreements between the property owner and the tenant, i.e.,

$$Vol_{it} = \frac{\sum_{j=1}^{N_i} cash\ flow_{rent,j}|exit_{it} = 1}{N_i} \times S_{it}^{-1}. \tag{1}$$

I normalize the trading volume by the local rental housing stock S_{it} in the municipality i at time period t to account for the rental market size. The normalization makes the liquidity measures comparable across local markets with different supply-side restrictions of the construction sector. For some local markets, I have missing values because of the unavailability of the offered rental price data. However, I assume that the local liquidity is missing at random as the unobserved liquidity level is unrelated to the individual decision of the property owner to conceal the rent information. The transaction volume serves as a rough proxy for local rental market liquidity. For instance, Chordia, Subrahmanyam, and Anshuman (2001) use the trading activity as a simple liquidity measure in stock markets. In the context of rental markets, a low trading volume indicates a limited number of realized rent agreements between a local landlord and tenants.

Inventory-Based Measure: I follow Piazessi, Schneider, and Stroebel (2014) and include the market turnover rate, and the inventory share for each local market. The turnover rate V_{it} is defined as the total number of rental offers in market i that exit the online platform per period relative to the total rental stock. A low turnover rate indicates a high non-execution risk for the landlord in terms of high a vacancy rate, a long time on the market, and higher implied opportunity costs of lost income from rental cash flows. The turnover rate also provides implications about the market activity for the potential

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tenants. Piazessi, Schneider, and Stroebel (2014) use the inverse of the turnover rate multiplied by 100 to determine the average number of years for a rental unit to change the tenant. Competition for limited amount of available space implies that, once rental units are removed from the market because of realized rent agreements, it is more difficult for remaining searching households to find rental units in the local rental market. This can be implied from the low fluctuation of households between rental units once they signed a rent contract, measured by the turnover rate.

The average local market inventory is defined as

$$\mu_{it} = TOM_{it} \times V_{it} \times S_{it}, \tag{2}$$

where TOM_{it} reflects the average duration between the initial release of a listing and its exit from the trading platform, i.e., the expected time on the market, V_{it} represents the per year turnover rate, and S_{it} denotes the annual total rental housing stock in the market i. The inventory share is specified as

$$I_{it} = \frac{\mu_{it}}{S_{it}} \tag{3}$$

and captures the fraction of rental vacant space in the local market. This measure gives an indication about the availability component of liquidity that is particularly relevant for the tenant. There are two possible channels at work: A larger share of available vacant space can be either driven by a limited demand from potential tenants, i.e., reflecting a higher non-execution risk for landlords, or because of a high relocation of potential tenants across rental units. The former channel implies scarce demand, the latter implies a large trading activity from the demand-side.

Duration-Based Measures: The duration-based illiquidity measures are particularly relevant for the landlord, as a higher expected time on the market is related to a higher implied opportunity costs in terms of not realized rental income. I compute the

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expected time on the market for each municipality. This measure captures the cost of non-execution for landlords who provide liquidity but whose released offers are not removed from the trading platform because of the imbalance between liquidity supply and demand. A higher duration is associated with an increase in the implicit opportunity cost of lost rental income for the property owner. Foucault, Kadan, and Kandel (2005) find a negative correlation between the cost of non-execution and liquidity demand. In a first step, I regress the time on the market d_{ijt} of the unit j in market i offered at time t on the vector of hedonic attributes $X_{i,j}$, i.e.

$$log(d_{ijt}) = X_{i,j}^{'}\beta + \varepsilon_{ijt}, \tag{4}$$

assuming a normal distribution of the error term after the log-transformation. The regression captures the effect of the property-specific price fundamentals on the individual time on the market. I show the regression results in Table D.1 in the Internet Appendix. In a second step, I use the predicted values of the individual duration, $\widehat{d}_{ijt}$, to compute the systematic, market-specific expected time on the market,

$$\widehat{TOM}_{it} = N^{-1} \sum_{j=1}^{n} \widehat{d}_{ijt}, \tag{5}$$

determined by their cross-sectional average for each local market i in period t. For comparability, I also normalize the expected duration by the rental stock of the local market.

Related to the standard Amihud (2002) illiquidity measure, I compute a version that accounts for the specific characteristics of rental markets.[9] I measure the systematic impact of the realized transaction volume on the expected time on the market,

$$ILLQ_{it} = \frac{TOM_{it}}{Vol_{it}} \times S_{it}^{-1}. \tag{6}$$

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[9]The Amihud (2002) illiquidity ratio is defined as the absolute stock price change relative to the transaction volume in a trading period, averaged over the total number of trading periods. This measure captures the sensitivity of the market price to the trading volume. For instance, a high value of the Amihud ratio is related to a high level of market illiquidity.

This measure serves as a proxy for the local market illiquidity from the perspective of the landlord and captures the extent to which the realized transaction volume has a systematic impact on the expected time on the market. For instance, a systematic lower transaction volume in a thinly traded market is related to an increase in the average duration of the listed offers. In a cross-sectional comparison, a larger value of the ratio, for instance, indicates an oversupply of rent offers in a systematic less active rental market, channeled either through higher costs of non-execution, lower trading activity because of limited demand from tenants, or both (Foucault, Kadan, and Kandel (2005)).

Table 2 compares the different liquidity measures. Panel A depicts the mean, standard deviation, as well as the minimum and the maximum for each liquidity measure. Panel B provides the correlation matrix of the proxies. The trading volume, inventory share, and turnover rate are positively related to each other and show a negative association with the illiquidity measures (expected time on the market and the duration impact) from the perspective of the landlord.

[INSERT TABLE 2 HERE]

In the next step, I follow Pastor and Stambaugh (2003) and compute the market-wide liquidity as the cross-sectional average of the individual local market levels to show the evolution of liquidity over time. I rank the average level based on the quartiles of the geographic distance distribution from the agglomeration center to the municipality in the commuting area with the largest distance to the center. Figure 3 illustrates the time series variation of the four different quartiles (with cutoff values at 25%, 50%, and 75% of the distance distribution) for each individual liquidity measure. With each change of the classified group further away from the urban center, e.g., a change in the range from the first to the second quartile to the range from the second to the third quartile, we observe a negative shift in the liquidity level. For the illiquidity measures, a positive shift can be observed. The market-wide rental market liquidity also slightly decreased in 2009, as a

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potential consequence of the recent financial crisis.[10]

[INSERT FIGURE 3 HERE]

3.2 Agglomeration Effects and Control Variables

In this section, I disentangle urban agglomeration externalities from local market characteristics and municipality-based control variables. As a proxy for the attractiveness of the local agglomeration centers, I use the Credit Suisse Site Quality Index. The index compares geographic regions in Switzerland based on their competitiveness. The criteria cover economic factors, such as tax incentives for local firms and households, the availability of qualified labor, and existing infrastructure, e.g., the connectivity to a local airport. The Site Quality Index is annually released since its launch in 1997, with a fully methodological update provided in 2004, the starting period of the dataset.

To isolate the systematic effect of agglomeration externalities from nearby located urban centers on the local market liquidity, I control for market-specific heterogeneity. Following the recent literature, I capture local market characteristics that have an impact on the mobility decision of households. These confounding factors affect the attractiveness of local rental markets and indirectly influence the local market liquidity that is endogenously determined by the location choice of the households. I use lagged values of the control variables to avoid the endogeneity problem. Table 3 presents a descriptive summary of the covariates.

Local Rent Level: Liquidity and rental prices are jointly determined. I control for the average local market rent level to mitigate concerns about spurious correlation that might arise from the rent. This argumentation derives from the spatial equilibrium condition of the standard urban rent gradient model. Households compare different rent offers.

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[10]I also provide Box-Whisker plots in Figure D.2 in the Online Appendix where the local liquidity is categorized according to the the 10%-quantiles of the distance distribution from the urban agglomeration center. The upper and lower quartiles (75%-, and the 25%- quantiles, respectively) and the median of the cross-sectional liquidity distribution indicate a negative relation to the geographic distance.

Their location choice follows the compensation principle. Households who face higher commuting costs to travel to the urban center, as implied by a larger geographic distance, require a compensation by lower rents. The spatial equilibrium condition must hold to ensure that households are indifferent between different locations. If the compensation principle is violated, individual households have an incentive to relocate. I use the market average as a proxy for the individual rent offered by the landlord since rent offers that are too high compared to the local market are less competitive. Additionally, I choose the following local market characteristics:[11]

Vacancy Rate: I control for the annual vacancy rate. This control variable captures the supply of vacant space. Markets are heterogeneous with respect to the supply of available rental units. The structural vacancy rate is related to search frictions that cause a systematic mismatch between landlords and tenants (Wheaton (1990)). A high structural vacancy rate might also imply an oversupply of rental units of low quality.

Supply Inelasticity: Saiz (2010) proposes geographic land constraints as a proxy for inelastic housing supply. Similarly, Glaeser, Gyourko, and Saks (2005) highlight the importance of policy-induced zoning restrictions and land use regulations on local construction growth and house prices. I use the percentage share of undevelopable land to capture potential housing supply inelasticity. Technically, the supply inelasticity can also be removed by market fixed effects. However, I include the share of undevelopable land as a control variable for two reasons: First, geographic distance as main explanatory variable is time-invariant and its effect on local market liquidity would be removed by the fixed effects. Second, explicitly controlling for the the share of undevelopable land captures the sensitivity of local liquidity to geographic supply restrictions.

Local Amenities: The set of control variables also includes public and private investments in the local infrastructure. The investments contain new construction of transportation networks, housing, and commercial real estate. For instance, new space for

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[11]The data are collected from the Swiss Bureau of Statistics.

commercial use attracts locating firms and human capital based qualified labor force, thereby improving the business location of the market (see, e.g., Chen and Rosenthal (2008)). Infrastructure investments also include schooling and culture that serve as a proxy for local amenities and might influence households in their location choice.

Population and Cross-Border Commuting: I consider the demographic trend in the municipality. Population growth reflects the local demand-side of the housing market. To account for different economic growth rates and corresponding income, I control for the cross-sectional variation across local market based inflow of qualified workforce. For this, I use the annual rate of cross-border commuters residing in neighboring municipalities.

[INSERT TABLE 3 HERE]

4 Identification Strategy

This section presents the identification strategy to isolate the liquidity gradient on local rental markets. In a first step, I describe the underlying assumptions of the empirical analysis that must be fulfilled. In a second step, I discuss potential pitfalls of the identification strategy and I provide several solution strategies to address them.

I regress the following linear model specification

$$Liquidity_{it} = \beta_0 + Distance_i\beta_1 + X'_{it}\delta + \varepsilon_{it}, \tag{7}$$

where market liquidity in municipality i at period t is regressed on the geographic distance to the nearby located urban agglomeration center (Zurich, Geneva, Lausanne, Basel, and Bern). The identification strategy is based on the conditional independence assumption, or selection of observables, that are captured by the vector X_{it}. Based on the selection of observables, I rule out any potential endogeneity between the error term ε_{it} and the distance measure $Distance_i$ (see, e.g., Imbens (2004)). Conditional on adjusting for all ob-

served local market characteristics, systematic differences in the market liquidity between the municipality i and the urban center are only related to the geographic distance.

The conditional independence assumption is required to mimic an experimental setup, under which the variable of interest is ideally randomly assigned to the local markets. Potential limitations of my research design arise from the fact that the geographic distance between the urban center and the local market is not randomly assigned, but is an immutable characteristic. However, local liquidity is an equilibrium outcome that is endogenously determined by the location choice of individual households. From a theoretical perspective, the location choice is exclusively influenced by market-specific characteristics and local amenities. According to the compensation principle, individuals are indifferent between different locations as long as higher commuting costs are compensated by lower rent levels. The compensation principle provides a theoretical rationale for the conditional independence assumption. Conditional on the observed covariates, that influence households in their decision to relocate across different local markets, the geographic distance from the urban center is irrelevant for the determination of the local market liquidity.[12]

From an empirical perspective, the location choice determines the exact timing at which households perceive the immutable geographic distance from the local municipality to the urban center as their individual commuting costs. For instance, Greiner and Rubin (2011) argue that the exact timing at which the immutable regressor is perceived by the decision-maker justifies the use of pre-determined covariates as control variables. Following this argumentation, I exploit the timing at which the local market liquidity is endogenously determined in equilibrium by the participants. More precisely, I condition only on pre-determined observable local market characteristics that are not influenced by the location choice of the individual households.

In the following, I address further potential pitfalls of the conditional independence

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[12]The exogeneity of the regressor, i.e., $Distance \perp\!\!\!\perp Liquidity_{it}(d)|X_{it}$, as implied by the selection on observables, follows directly from the empirical model-based mean independence assumption, $E[Liquidity_{it}(d)|Distance, X_{it}] = E[Liquidity_{it}(d)|X_{it}]$.

assumption in more detail. A potential violation of the assumption would contaminate the estimated coefficients. I also propose several solution strategies to remedy the implied consequences for the empirical analysis.

Unobserved Covariates: The identification strategy crucially depends on the selection on observable control variables. A potential source of endogeneity arises from unobserved market characteristics that simultaneously affect the market liquidity and the geographic location of the municipality relative to the agglomeration center. I include locational and geographic categorical variables to account for the geographic heterogeneity across local municipalities. For instance, some households might be willing to accept larger commuting costs to the agglomeration center since they have a stronger preference for living in rural areas rather than in large cities. Households who prefer to reside near forests, mountains, and lakes might have a higher willingness to pay for housing. I include dummy variables for municipalities that are located in mountainous landscapes. I also control for municipalities that adjoin to lakeside at the border.[13] Border dummies capture municipalities that are direct neighbors to foreign countries. I also control for systematic differences across urban and rural rental housing markets. Additional dummy variables capture the degree of urbanization, i.e., whether the municipality is more rural or belongs to a specific agglomeration area. I control for language borders to capture differences in the cultural background. The location choice of households might also be influenced by their preference to move to neighborhoods that are perceived as culturally familiar. Furthermore, the cross-sectional variation in the market liquidity might also be driven by the canton-specific heterogeneity.[14] For instance, households have incentives to move to municipalities within cantons with higher economic growth perspectives or preferable tax regimes. To account for these differences, I include the canton-level unemployment rate, the GDP growth rate, and the tax rate based on the median gross income of CHF

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[13]For instance, house prices might be higher around small municipalities that adjoin Lake Constance at the German border and Lake Leman around Geneva and Lausanne at the French border.

[14]The federal system of Switzerland assigns all municipalities to 26 cantons. The cantons are political units at the state-level that constitute the Swiss Confederation.

50.000, conditional on the marital status and the number of children. Alternatively, I exploit canton-fixed effects to mitigate the potential endogeneity arising from time-invariant unobservable components. The selection on additional observable confounding factors mitigates the potential endogeneity problem. It does not account for unobserved market characteristics. However, the conditional independence assumption also holds when the location choice of households might be influenced by unobserved market conditions, but these conditions are unrelated to the explanatory variable of interest in the research design (see, e.g., Imbens (2004), Imbens and Wooldridge (2009)).

General Equilibrium Effects: Another limitation arises from potential general equilibrium effects between local markets. From theoretical perspective, the validity of the identification strategy is justified by the imposed spatial equilibrium assumption under which individuals are indifferent between locations. Particularly, I rule out any interaction effects between the geographic distance to the local market and the liquidity in the agglomeration center. This is arguably a strong assumption. However, under the compensation principle implied by the spatial equilibrium condition, the individual location choice is not affected by the geographic distance.[15]

I also empirically address the problem of cross-sectional dependence by the spatial aggregation level of the liquidity measures. First, local liquidity is determined at the municipality level. Therefore, I capture the potential spatial interaction effects that might be related to the relocation of households within the local neighborhood as this is translated into the endogenous local liquidity measures. Second, the added controls at the canton-level and the country-wide common factors absorb any potential spatial dependence across municipalities (e.g., Sarafidis and Wansbeek (2012)). For instance, I include the short-term interest rate and the immigration from other countries to control for country-wide and global macroeconomic conditions that jointly affect the local rental

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[15]As implied by the spatial equilibrium assumption, I rule out any potential relocation of individual households that cause potential interaction effects between the local markets. This exclusion restriction is required for the Stable Unit Treatment Value Assumption (SUTVA) to hold. For an overview, I refer the reader to Imbens and Wooldridge (2009).

markets.

Covariate Balancing Propensity Score (CBPS): To improve the comparability across the municipalities, I compute the optimal balancing weights from the propensity score to balance across the local markets. Following Imai and Ratkovic (2014) and Fong, Hazlett, and Imai (2015), I apply the non-parametric CBPS approach to directly minimize the relation between the local market characteristics and the continuous distance measure. Imai and Ratkovic (2014) propose the generalized propensity score to circumvent the potential misspecification of the estimated propensity score. The generalized propensity score is defined as the conditional distribution of the geographic distance, conditional on a vector of control variables. They exploit the fact that the propensity score balances across the set of covariates. Fong, Hazlett, and Imai (2015) propose a parametric as well as non-parametric approach to estimate the optimal balancing weights. I compare the empirical results and contrast them to the propensity score analysis of Hirano and Imbens (2004). I discuss all three approaches in more detail in Section B of the Internet Appendix.

5   Estimation Results

This section presents the empirical results. In a first step, I provide empirical evidence for the liquidity gradient hypothesis. In a second step, I show that the impact of urban agglomeration externalities on local rental markets is decreasing with increasing distance from the urban center. Furthermore, positive agglomeration externalities in the urban center are related to a systematic liquidity risk in more distant local municipalities. I also provide empirical evidence of a illiquidity discount in local rental housing markets and how this negatively affects the cash-flow earnings of property investors.

5.1 Liquidity Gradient

Table 4 provides empirical evidence for the liquidity gradient in rental housing markets. I find a negative relation between the distance from municipalities to the urban center and the local market liquidity. Local liquidity is systematically higher in markets that are located nearer to the agglomeration center. The negative relation can be seen for the transaction volume, the inventory share, and the turnover rate (see Columns (1) to (3)). The average time on the market and the duration impact of trading volume (Columns (4) and (5)) are positively related to the distance measure. For all measures, the liquidity gradient hypothesis can be empirically verified. The estimated coefficient of the liquidity gradient is economically significant and indicates the hypothetical slope in the relation between liquidity and geographic distance.[16] The inference is based on clustered standard errors to account for potential spatial dependence across local markets.

Given the control variables, an additional kilometer in distance from the agglomeration center decreases the trading volume in the local market by 2.7%. This liquidity proxy captures the overall trading activity in the market. However, the implications are the same for market participants. From the perspective of the landlord, local liquidity decreases the further away the rental market is located from the agglomeration center. In these markets, the landlord is confronted with a higher expected time on the market, because of the limited liquidity demand from potential tenants. The expected time on the market increases by 0.7%. Similarly, the duration impact increases by 3.9%, reflected in a higher time on the market and a lower trading activity. It is important to remind that for landlords the liquidity demand is the driving factor for the released rent offers to be removed. Liquidity supply, i.e., the availability of rent offers, is crucial for tenants. The estimated coefficients for the inventory share and the turnover rate are -0.028 and -0.025, respectively. Intuitively, a low turnover rate in more rural markets implies that

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[16]In the Internet Appendix I also test for a nonlinear distance effect. However, the estimated nonlinear effect is neither economically nor statistically significant. I therefore conclude that the liquidity gradient is linear.

potential tenants are confronted with less vacant rental space. Once rental offers are removed from the market, it is more challenging for them to find vacant rental units because of long-lasting rent agreements.[17] A negative inventory share implies that the decrease in the turnover rate offsets the increasing time on the market for landlords. Economically, there is a systematic mismatch between the housing quality of the remaining vacant space in local rental markets with greater distance to the agglomeration center and the preferences of households searching for rental units.

I include the (lagged) average market-specific rent level to control for spurious correlation. Therefore, I rule out that the liquidity gradient emerges merely from the rent gradient implied by the compensation principle. The vacancy is positively related to the market liquidity. The local market conditions, i.e., population growth and the percentage of undevelopable land are also positively correlated with liquidity. The signs of the estimated coefficients are in line with the economic intuition. Population growth captures the demand-side from potential tenants who search for rental units. The share of undevelopable land denotes a supply-side restriction of the market. A larger share is related to a denser space occupied by rental units and ensures the realization of rent agreements at lower search and matching costs. Similarly, the attractiveness of local markets is captured by the relative change of annual commuters that are employed in the local labor market but who reside in neighboring municipalities. Similarly, investments in the local infrastructure by the private and public sector capture the growth perspectives of the local market. Both variables are positively related to the different liquidity measures.

I provide further robustness checks in Table D.3 in the Internet Appendix, where I also control for specific economic conditions at the canton-level, geographical characteristics, and locational amenities. Conditional on the set of additional factors, I still find evidence of the negative relation between local market liquidity and the geographic distance to the urban agglomeration center. The estimated coefficient of the liquidity

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[17]The tenancy law in Switzerland provides incentives for tenants not to terminate their rent contracts by keeping contractually determined rents fixed.

gradient is similar in magnitude compared to the baseline result in Table 4. Therefore, I conclude that there is no potential omitted-variables bias of the estimated liquidity gradient.

[INSERT TABLE 4 HERE]

To improve the comparability across local markets, I non-parametrically estimate the covariate balancing propensity score and use the inverse weightings to balance across local municipalities in terms of the market characteristics. The estimates are based on the weighted least square regression, where the weights are directly calculated from the propensity score. Table 5 shows the results of the non-parametric propensity score approach (np CBPS) for all liquidity measures. I contrast the results of the non-parametric approach to the parametric approach (p CBPS) and compare the outcome to the Hirano and Imbens (2004) approach (HI). Both, the magnitude and the sign of the estimated coefficients are similar compared to the baseline regression in Table 4. The Hirano and Imbens (2004) approach uses only the propensity score as a control variable, while I also include the baseline covariates as additional controls in the parametric and the non-parametric regression of Fong, Hazlett, and Imai (2015). To compute the propensity score, I use the urban dummy characteristics (whether the municipality is located within the commuting area of another agglomeration area, the municipality is isolated, or belongs to a rural area outside of the agglomeration center) and the canton-based unemployment rate , in addition to the baseline covariates (vacancy rates, the share of undevelopable land, the annual rate of cross-border commuters, investments in local infrastructure).

Based on the improved comparability across local markets, I support the hypothesis of the liquidity gradient for all liquidity measures. For instance, an increase in distance from the agglomeration center is related to a decrease in local market liquidity of 3.6% based on the Hirano and Imbens (2004) approach, 2.2% based on the weighted least square approach with the parametric specification of the propensity score, and 2.7% based on the estimates using the non-parametric specification of the propensity score.

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[INSERT TABLE 5 HERE]

5.2 Agglomeration Externalities

In this section, I show the impact of agglomeration externalities on local market liquidity. To estimate the unobservable agglomeration effect, I specify the following regression model:

$$Liquidity_{it} = \beta_0 + distance_i\beta_1 + SQI_t\beta_2 + distance_i \times SQI_t\beta_3 + X_{it}'\delta + \varepsilon_{it} \qquad (8)$$

The identification is based on the interaction term between the geographic distance and the Site Quality Index (SQI_t) related to the nearby located urban center. I exploit the variation in the performance of the agglomeration center over time and use the cross-sectional distance from the center to capture its effect on nearby located rental markets.

Table 6 presents the results for the different liquidity measures (see Columns (1) to (6)). Overall, I find an attenuating agglomeration effect on market liquidity with increasing distance of the municipality from the urban center. A higher attractiveness of the urban center has a positive impact on the liquidity in its own rental market. For instance, an increase in the competitiveness as a business location with superior infrastructure compared to other municipalities attracts additional firms and qualified labor force. With increasing distance from the center, the positive effect attenuates. For example, consider the effect on the trading volume between the urban center and a more distant local market: The agglomeration effect increases the trading volume by 43.6% in its own rental market. However, relative to the increase in liquidity in the urban center, the impact of the agglomeration externalities on trading volume decreases by 1.5%-points with each additional unit in distance from the center. Similar effects can be observed for the other liquidity measures, except for the market-specific average time on the market.[18]

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[18]The Quality Site Index captures a positive externality effect. In Table D.4 in the Internet Appendix I use the amount of home burglaries per 1000 residents in the agglomeration center as a negative

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[INSERT TABLE 6 HERE]

To elaborate the effect of agglomeration externalities on the systematic liquidity risk over time, I test for the relation between the local market liquidity and the attractiveness of the urban center. The Site Quality Index serves as a proxy for the economic performance of the urban center. I exclude the municipalities that are directly assigned to the location of the center and use municipality-based fixed effects to control for the unobserved market heterogeneity. The within-estimator captures the variation of the liquidity within the local market over time. Table 7 shows the negative relation between the Site Quality Index and the liquidity proxies (Columns (1) to (3)) and a positive relation to the measures of market illiquidity (Columns (4) and (5)). Positive agglomeration externalities in the center absorb liquidity from local rental markets in the commuting area. An increasing attractiveness of the agglomeration center is related to a decline in the rental market liquidity of nearby located municipalities over time, implying a systematic illiquidity risk.[19]

The regressions also include controls for the market-wide macroeconomic condition. An increase in the canton-level unemployment rates leads to a higher exposure of the tenants to labor market shocks, potentially increasing the risk of rental payment defaults. This effect reduces the liquidity risk over time as the implied relocation of households serves as an impulse for the liquidity supply in the rental market. The nominal interest rate is negatively related to the local market liquidity over time. For instance, higher interest rates might be transmitted to rent inflation, driven by potential debt service costs passed on from the landlord to the tenant, that reduces the liquidity supply of potential tenants. Similarly, periods of low interest rates, associated with low expected inflation, might cause potential transaction price run-ups in the owner-occupied housing

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agglomeration externality. As expected, the estimated signs of the coefficients are reversed. A higher crime rate decreases the market liquidity in the urban center and the negative impact mitigates with increasing distance of the local market from the center.

[19]Table D.6 in the Internet Appendix provides further support of the implied negative spillover effect between market liquidity in the agglomeration center and the absorbed liquidity level in nearby located municipalities. I use the lagged liquidity level in the center as explanatory variable and find evidence of liquidity dry-outs in rental markets within the commuting area.

market (see, e.g., Brunnermeier and Julliard (2008)). In the long-term, this makes renting relatively more affordable than buying. The economic channels of how net immigration affect the different liquidity proxies are more ambiguous. The migration inflow from other countries leads to an additional demand for rental space and increases the transaction volume, while it lowers the inventory share and the turnover rate as the liquidity supply. The higher liquidity supply leads to an excessive supply as the liquidity demand is fixed because of the sluggish reaction of the construction sector. Furthermore, the higher demand for rental space also reduces the average duration of listed rent offers due to the liquidity supplied by the potential tenants.

[INSERT TABLE 7 HERE]

5.3   Illiquidity Discount in Rental Housing Market

Subsection 5.1 provides empirical evidence of a negative relation between the distance from the urban agglomeration center and the local liquidity in rental markets. In subsection 5.2 I show how positive agglomeration externalities in urban centers increase the liquidity risk in more distant local rental markets. This section focuses on buy-to-let investments of market participants, who specifically purchase properties to rent them out. To learn about the relationship between the rental cash flow stream and local market liquidity is particularly important for households who receive rental cash flows as a significant source of their household wealth and invest in rental units as part of their private pension plan. I show how local market liquidity is related to the amount of current income an investor receives per currency unit of the property value. For this purpose, I compute the capitalization rate, $cap_{it} = \frac{R_{it}}{P_{it}}$, that is defined as the rental cash flow divided by the underlying property value.

The dataset does not include the corresponding property values for the offered rental units. To compute the capitalization rate, I uniquely match the listed rent offers with the offered purchase price of comparable owner-occupied apartment. The matching algorithm

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is based on the set of hedonic characteristics. In an additional robustness check, I also include the geographic location (based on the longitude and latitude at one digit) in the algorithm. The empirical result is similar to the presented specification without taking into account the location, but the sample size of the matched data is smaller. I follow a one-to-one matching algorithm based on 449,299 listed apartments for sale. The average purchase price of the apartments equals CHF 595,000. The prices range from CHF 13,000 to CHF 31,000,000.[20]

I regress the rent-to-price ratio of properties on the lagged local market liquidity. Purchasing a property is time-consuming, involving high search and matching costs. It is therefore rational to assume that the investment decision of an investor is based on the local liquidity of the previous year. The use of lagged values also mitigates potential endogeneity issues between the capitalization rate and the local market liquidity. The model specification includes the set of housing characteristics as controls. I capture the return of the country-specific stock index and the bond performance, that are relevant alternative investment opportunities for small, private investors. Country-specific and local market conditions are included to reflect the potential growth perspective of the invested properties. To allow the flexibility in the functional form, I include nonlinearities (squared terms) and possible interactions between the control variables (up to 308 control variables). I include all confounding variables that jointly affect the capitalization rate and the market liquidity. To circumvent the omitted-variable bias, I estimate a reduced-form relation between the market liquidity and the set of controls to pre-select those variables that are highly correlated with the endogenous variable and also show a predictive power for the explanatory variable (see, e.g., Belloni, Chernozhukov, and Hansen (2014a)). Table 8 presents the regression results based on different pre-selection methods.[21] The estimated coefficients are similar to those from the the baseline OLS regression without pre-selection.

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[20]As proxy for the realized transaction price, I use the offered purchase price that might be systematically upward biased compared to the underlying property value. As a consequence, the capitalization rates might suffer from a systematic downward bias.

[21]I discuss the different estimation strategies in more detail in the Online Appendix. Table D.7 therein provides an overview of the estimated coefficients from the baseline OLS model.

I find a positive relation between market liquidity and the capitalization rate. The rent-to-price ratio is systematically lower in municipalities with higher rental market illiquidity, e.g., a higher expected time on the market from perspective of the landlord. This is in line with the economic intuition. Landlords offer a rental price discount on the released rental units to attract the liquidity demand from potential tenants in systematically thinly traded, less attractive markets. From an asset pricing perspective, the capitalization rate can be interpreted as the discount rate. The illiquidity discount reduces the current yield component, the investor as a landlord can obtain per currency unit of the underlying property value. This implication follows from the Gordon-Growth type discount model $P_{it} = \frac{R_{it}}{r-g}$, where the current yield equals the required expected rate of return r of the investment less the future potential growth component g (see, e.g., Plazzi, Torous, and Valkanov (2010)). Piazessi, Schneider, and Stroebel (2014) find a similar effect for the owner-occupied housing market. They show that buyers require a price discount for the potential search costs that are attributed to the market illiquidity.

[INSERT TABLE 8 HERE]

6   Conclusion

This paper provides a systematic study of the relation between liquidity in rental housing markets and urban agglomeration effects. Online rental housing market platforms can be compared to the limit order book in stock markets. Conceptionally, landlords provide liquidity by released rent offers. Tenants screen these listings and decide whether to accept the offer. Potential tenants demand liquidity. Realized rent agreements between the landlord and tenants remove liquidity from the market as the released offer leaves the online market platform. I propose and compare different liquidity measures that are suitable to capture the specific characteristics of the rental housing market. Each measure focuses on a different dimension of market liquidity, such as the transaction activity, the

inventory risk, and the non-execution risk. The liquidity proxies should help market participants to learn about the rental market.

The paper also contributes to the understanding of the systematic effect of urban agglomeration centers on local market liquidity. I first provide empirical evidence of the liquidity gradient hypothesis, stating that, with increasing distance from the urban center, local market liquidity is decreasing. The results are robust conditional on a set of specific local market characteristics, as well as economic conditions on the municipality level. Second, the impact of agglomeration externalities in urban centers on local rental markets also attenuates with increasing distance to the center. Third, I show that a positive performance of the agglomeration center is related to a systematic liquidity risk in more distant local markets as the agglomeration center absorbs the liquidity from less attractive local housing markets. I also find empirical evidence that in thinly traded, illiquid rental markets property investors earn systematic lower capitalization rates.

The results have important implications for the market participants and provide relevant insights for policy implications. For instance, landlords are exposed to the systematic non-execution risk, i.e., a higher time on the market, in more distant local markets. This is of particular importance, as the rental income contributes to the household wealth and provides a source to the old-age provision. Simultaneously, tenants are confronted with a systematic lower availability of rent offers in more distant, rural areas. This implies that because of the limited rent offers, there is a systematic mismatch between the housing quality of available rental units offered by landlords and the preferences of the remaining potential tenants that cannot be solved.

From a policy perspective, the empirical results suggest that, in order to improve the demand from tenants in less attractive, thinly traded local rental markets, specific investments in the local infrastructure and more efficient commuting times to the urban centers should be the focus of the policy maker instead of active interventions and corrections in thick rental housing markets. Lower capitalization rates that can be obtained

by investors in illiquid markets provide no incentive for the construction sector to provide additional rental space that might solve the mismatch between the housing quality of limited vacant rental units and the preferences of remaining households searching for available rental space.

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Table 1: Hedonic Characteristics

This table shows the descriptive summary of the hedonic characteristics. All variables are based on listed rent offers on online trading platforms from 2004 to 2015. I remove all entries with a time on the market that exceeds 1000 days. The net rent offer is measured in CHF per month. Based on the listings, I construct hedonic dummy variables, such as access to a balcony, a garden, a terrace, or how many rental units can be reached by a lift. The Swiss Minergie certificate captures the share of energy efficient building construction in the sample. The hedonic characteristics also include architectural style (e.g., attica, studio, loft) and locational amenities. The dummy variable Near Nature captures the share of apartments that are located nearby a lake, a forest, or contain a view of the mountains.

	Mean	Std.Dev.	Min	Max	Obs.
Duration	53.24	77.36	1	1000	2183944
Rent Offer	1665.97	924.51	201	15000	2183944
Living Surface	84.74	36.60	11	400	1643638
Rooms	3.35	1.24	1	10	2128886
Minergie Certificate	0.02	-	0	1	2183944
Balcony	0.57	-	0	1	2183944
Terrace	0.11	-	0	1	2183944
Garden	0.16	-	0	1	2183944
Shared Apartment	0.001	-	0	1	2183944
Near Nature	0.19	-	0	1	2183944
Duplex	0.05	-	0	1	2183944
Rooftop	0.05	-	0	1	2183944
Attica	0.03	-	0	1	2183944
Studio	0.02	-	0	1	2183944
Loft	0.01	-	0	1	2183944
Furnished	0.05	-	0	1	2183944
Wheelchair Access	0.05	-	0	1	2183944
Lift	0.30	-	0	1	2183944
Seasonality	0.50	-	0	1	2183944

Table 2: Descriptive Summary and Correlation Matrix of Liquidity Measures

This Table compares the different liquidity measures. Panel A shows the mean, the standard deviation, as well as minimum, and maximum values of the different liquidity measures (the transaction volume, the inventory share, the turnover rate, the average time on the market (Average TOM), and the duration impact of trading volume (Duration Impact)). Panel B depicts the correlation matrix of the different liquidity measures. All measures are computed at an annual level and are determined in log. The sample ranges from 2004 to 2015.

Panel A: Summary Statistics

	Mean	Std.Dev.	Min	Max	Obs.
Trading Volume	5.54	1.26	-0.03	10.66	21877
Inventory Share	-6.48	1.82	-13.51	1.79	22116
Turnover Rate	-10.41	1.69	-13.51	-3.06	24357
Average TOM	-1.37	1.18	-7.73	3.81	20785
Duration Impact	-10.95	2.86	-24.78	-2.40	21877

Panel B: Correlation Matrix

	Trading Volume	Inventory Share	Turnover Rate	Average TOM	Duration Impact
Trading Volume	**1.000**				
Inventory Share	0.592	**1.000**			
Turnover Rate	0.660	0.920	**1.000**		
Average TOM	-0.044	-0.675	-0.723	**1.000**	
Duration Impact	-0.079	-0.823	-0.903	0.855	**1.000**

Table 3: Descriptive Summary and Correlation Matrix of Control Variables

This Table compares the market-specific covariates. Panel A provides a descriptive summary of the local covariates. The columns indicate the mean, the standard deviation, the minimum as well as the maximum values of the Quality Site Index in the five local urban agglomeration centers (Zurich, Geneva, Lausanne, Basel, and Bern) and the market-specific characteristics of the local municipalities within the commuting area of the centers. Panel B indicates the correlation structure. Growth rates are determined as percentage changes. The sample ranges from 2004 to 2015.

Panel A: Summary Statistics					
	Mean	**Std.Dev.**	**Min**	**Max**	**Obs.**
Site Quality Index (SQI)	1.13	0.87	-0.30	3.30	11283
log(Rent)	7.50	0.24	6.53	9.37	10471
Vacancy Rate	0.05	0.08	0.00	0.94	12277
Undevelopable Land	0.20	0.17	0.02	0.98	12705
Δ Infrastructure	0.07	1.23	-9.42	11.60	12318
Δ Population	0.01	0.03	-0.28	0.33	12339
Δ Commuter	0.04	0.37	-3.01	3.82	12234

Table 3 continued.

Panel B: Correlation Matrix	Site Quality Index	log(Rent)	Vacancy Rate	Undevelopable Land	Δ Infrastructure	Δ Population	Δ Commuter
Site Quality Index	1.000						
log(Rent)	-0.045	1.000					
Vacancy Rate	0.252	-0.060	1.000				
Undevelopable Land	0.112	-0.109	0.115	1.000			
Δ Infrastructure	-0.012	0.010	-0.021	-0.006	1.000		
Δ Population	-0.031	0.066	0.003	0.013	-0.141	1.000	
Δ Commuter	0.022	0.019	-0.010	0.053	-0.008	0.018	1.000

Table 4: Liquidity Gradient

This Table shows the regression results of the liquidity gradient for the different local liquidity measures: trading volume (Column 1), the inventory share (Column 2), the turnover rate (Column 3), the average time on the market (Column 4), and the duration impact of trading volume (Column 5). The geographic distance is computed as the Haversine distance measured in kilometers to capture the shape of the earth. The covariates include the average rent level, measured in logs, the vacancy rate, population growth (Δ Population), the share of land supply restrictions (Undevelopable Land), the annual growth of commuters to the local market (Δ Commuter), and the annual percentage of private and public investments in the local infrastructure (Δ Infrastructure). All covariates are used at the lagged value to avoid the endogeneity problem. The sample includes all municipalities within the regional labor market of the five largest agglomeration centers in Switzerland (Zurich, Geneva, Basel, Lausanne, Bern). The definition of the regional labor market follows the Swiss Statistical office. Liquidity is measured for each municipality from 2004 to 2015. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	Trading Volume	Inventory Share	Turnover Rate	Average Time on the Market	Duration Impact
Distance	-0.027***	-0.028***	-0.025***	0.007*	0.039***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.008)
log(Rent)	0.556***	-0.652***	-0.669***	0.831***	1.087***
	(0.105)	(0.143)	(0.149)	(0.115)	(0.243)
Vacancy Rate	3.346***	2.392***	2.486***	0.994***	-1.405*
	(0.285)	(0.473)	(0.461)	(0.352)	(0.811)
Δ Population	6.845***	3.185***	3.148***	2.587***	-1.920
	(0.877)	(1.128)	(1.037)	(0.867)	(1.797)
Undevelopable Land	1.674***	5.067***	4.961***	-3.560***	-8.664***
	(0.283)	(0.361)	(0.359)	(0.305)	(0.626)
Δ Commuter	0.134***	0.249***	0.245***	-0.104***	-0.353***
	(0.074)	(0.055)	(0.045)	(0.036)	(0.077)
Δ Infrastructure	0.074***	0.055***	0.043***	0.030***	-0.034
	(0.013)	(0.020)	(0.016)	(0.011)	(0.027)
Observations	8605	8632	8632	8434	8605
Year dummies	Yes	Yes	Yes	Yes	Yes
Adj.-R^2	0.279	0.367	0.410	0.319	0.374

Table 5: Robustness with Propensity Score

This table shows the regression results of the liquidity gradient hypothesis for the different local liquidity measures: trading volume (Column 1), the inventory share (Column 2), the turnover rate (Column 3), the average time on the market (Column 4), and the duration impact of trading volume (Column 5). Estimates are based on the approach by Hirano and Imbens (2004) (HI), the weighted linear regression using the parametric (pCBPS), as well as the non-parametric (npCBPS) covariance balance propensity score as suggested by Fong, Hazlett, and Imai (2015). The geographic distance is computed as the Haversine distance in kilometers to account for the shape of the earth. The baseline covariates include the average rent level, the vacancy rate, population growth (Δ Population), the share of land supply restrictions (Undevelopable Land), the annual growth of commuters to the local market (Δ Commuter), and the annual percentage of private and public investments in the local infrastructure (Δ Infrastructure). All covariates are used at the lagged value. The generalized propensity score is based on the geographic distance regressed on the baseline covariates as well as urban dummy characteristics and the Canton-based unemployment rate. The sample includes all municipalities within the labor market region of the five largest agglomeration centers in Switzerland (Zurich, Geneva, Basel, Lausanne, Bern). Liquidity is measured for each municipality from 2004 to 2015. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	Trading Volume			Inventory Share			Turnover Rate		
	HI	pCBPS	npCBPS	HI	pCBPS	npCBPS	HI	pCBPS	npCBPS
Distance	-0.036***	-0.022***	-0.027***	-0.058***	-0.023***	-0.060***	-0.053***	-0.020***	-0.042***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.008)	(0.002)	(0.002)	(0.007)
log(Rent)		0.666***	0.564***		-0.614***	-1.052***		-0.595***	-0.941***
		(0.069)	(0.073)		(0.073)	(0.127)		(0.068)	(0.116)
Vacancy Rate		3.154***	3.198***		2.368***	2.889***		2.386***	2.638***
		(0.145)	(0.147)		(0.231)	(0.359)		(0.208)	(0.294)
Δ Population		6.783***	6.723***		2.911***	3.125***		2.894***	3.169***
		(0.559)	(0.533)		(0.746)	(1.035)		(0.657)	(0.755)
Undevelopable Land		2.466***	2.063***		5.881***	5.064***		5.863***	5.212***
		(0.087)	(0.091)		(0.116)	(0.173)		(0.106)	(0.157)
Δ Commuter		0.135***	0.155***		0.200***	0.294***		0.192***	0.257***
		(0.028)	(0.026)		(0.050)	(0.058)		(0.041)	(0.047)
Δ Infrastructure		0.079***	0.074***		0.062***	0.048		0.050***	0.036
		(0.014)	(0.014)		(0.021)	(0.034)		(0.068)	(0.027)
Propensity Score	-1.862			-22.077***			-20.245***		
	(1.355)			(2.133)			(1.919)		
Observations	8597	8604	8604	8624	8631	8631	8624	8631	8631
Adj.-R^2	0.116			0.098			0.098		
AIC		25165	24812		31488	32824		29262	30085

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Table 5 continued.

	Average Time on the Market			Duration Impact		
	HI	p CBPS	np CBPS	(HI)	p CBPS	np CBPS
Distance	0.026***	0.005***	0.007***	0.086***	0.029***	0.035***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)
log(Rent)		0.738***	0.767***		0.723***	0.862***
		(0.053)	(0.053)		(0.122)	(0.123)
Vacancy Rate		1.066***	1.157***		-0.994***	-0.784**
		(0.138)	(0.135)		(0.344)	(0.351)
Δ Population		2.334***	2.233***		-2.458**	-2.407**
		(0.560)	(0.550)		(1.238)	(1.227)
Undevelopable Land		-3.674***	-3.462***		-9.806***	-9.002***
		(0.095)	(0.091)		(0.198)	(0.200)
Δ Commuter		-0.098***	-0.127***		-0.342***	-0.416***
		(0.035)	(0.032)		(0.077)	(0.071)
Δ Infrastructure		0.028*	0.028*		-0.056	-0.052
		(0.016)	(0.015)		(0.036)	(0.036)
Propensity Score	15.974***			32.238***		
	(1.517)			(3.359)		
Observations	8431	8433	8433	8597	8604	8604
Adj.-R^2	0.052			0.098		
AIC		24667	24419		39056	38907

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Table 6: Effect of Urban Agglomeration Externalities on Local Market Liquidity

This table shows the effect of urban agglomeration economies on the different local liquidity measures: trading volume (Column 1), the inventory share (Column 2), the turnover rate (Column 3), the average time on the market (Column 4), and the duration impact of trading volume (Column 5). The geographic distance is computed as the Haversine distance in kilometers to account for the shape of the earth. The Credit Suisse Site Quality Index (SQI) captures the performance over time of the five largest urban agglomeration centers in Switzerland (Zurich, Geneva, Basel, Lausanne, and Bern). The covariates include the average rent level, the vacancy rate, population growth (Δ Population), the share of land supply restrictions (Undevelopable Land), the annual growth of commuters to the local market (Δ Commuter), and the annual percentage of private and public investments in the local infrastructure (Δ Infrastructure). The sample includes all municipalities within the labor market region of the five agglomeration centers in Switzerland. Liquidity is measured for each municipality from 2004 to 2015. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	Trading Volume	Inventory Share	Turnover Rate	Average Time on the Market	Duration Impact
Distance	-0.019***	-0.023**	-0.018**	0.005	0.022
	(0.007)	(0.009)	(0.008)	(0.006)	(0.013)
SQI	0.436***	0.356**	0.396**	0.008	-0.552*
	(0.108)	(0.178)	(0.160)	(0.137)	(0.286)
SQI $\times Distance$	-0.015***	-0.013*	-0.014**	0.001	0.0022**
	(0.004)	(0.007)	(0.006)	(0.005)	(0.011)
log(Rent)	0.364***	-0.699***	-0.653***	0.622***	0.828***
	(0.100)	(0.138)	(0.131)	(0.113)	(0.227)
Vacancy Rate	2.914***	1.598***	1.645***	1.550***	0.154
	(0.308)	(0.482)	(0.449)	(0.371)	(0.769)
Δ Population	3.655***	2.292**	1.895*	0.500	-2.956*
	(0.773)	(1.128)	(0.983)	(0.780)	(1.725)
Undevelopable Land	1.542***	4.834***	4.881***	-3.460***	-8.464***
	(0.241)	(0.364)	(0.353)	(0.313)	(0.631)
Δ Commuter	0.058**	0.163***	0.137***	-0.114***	-0.298***
	(0.027)	(0.051)	(0.041)	(0.032)	(0.071)
Δ Infrastructure	0.052***	0.057***	0.045***	0.011	-0.054*
	(0.013)	(0.020)	(0.016)	(0.012)	(0.028)
Observations	7675	7701	7701	7516	7675
Canton Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Adj.-R^2	0.454	0.446	0.511	0.425	0.472

Table 7: Effect on Liquidity Risk

This table shows the effect of the performance of urban agglomeration centers on the liquidity risk in local markets over time. The different liquidity measures are the trading volume (Column 1), the inventory share (Column 2), the turnover rate (Column 3), the average time on the market (Column 4), and the duration impact of trading volume (Column 5). The Credit Suisse Site Quality Index (SQI) captures the performance over time of the five largest urban agglomeration centers in Switzerland (Zurich, Geneva, Basel, Lausanne, and Bern). The covariates include the average rent level, the vacancy rate, population growth (Δ Population), the annual growth of commuters to the local market (Δ Commuter), and the annual percentage of private and public investments in the local infrastructure (Δ Infrastructure). Additional controls are the unemployment rate at the Canton-level (Δ Unemployment) and the growth rate of migration inflows at an aggregated country-level (Δ Migration). The sample includes all municipalities within the labor market region of the five agglomeration centers in Switzerland, excluding the municipalities that are directly related to the five agglomeration centers. The sample ranges from 2004 to 2015. Estimates are based on the within-estimator including market-specific fixed effects. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Trading Volume	Inventory Share	Turnover Rate	Average Time on the Market	Duration Impact
SQI	-0.175***	-0.137**	-0.148***	0.031**	0.233***
	(0.035)	(0.053)	(0.029)	(0.013)	(0.056)
log(Rent)	0.017	0.013	0.011	-0.049***	-0.118
	(0.065)	(0.082)	(0.059)	(0.017)	(0.094)
Vacancy Rate	0.700***	0.526*	0.453***	0.255***	0.142
	(0.171)	(0.282)	(0.153)	(0.073)	(0.245)
Δ Unemployment	-0.225***	-0.128*	-0.109***	-0.014	0.153**
	(0.041)	(0.070)	(0.037)	(0.015)	(0.077)
Δ Population	0.239	0.904	0.314	-0.274*	-0.920
	(0.519)	(0.755)	(0.453)	(0.146)	(0.712)
Δ Infrastructure	0.024**	0.030*	0.022**	0.005	-0.016
	(0.012)	(0.016)	(0.011)	(0.003)	(0.016)
Interest Rate	-0.098***	-0.037***	-0.038***	0.035***	0.164***
	(0.008)	(0.011)	(0.007)	(0.003)	(0.012)
Δ Commuter	-0.016	-0.022	-0.008	-0.007	0.009
	(0.020)	(0.035)	(0.019)	(0.007)	(0.035)
Δ Migration	-0.948	-12.167***	-11.696***	-9.700***	-17.565***
	(1.029)	(1.425)	(0.920)	(0.361)	(1.503)
Observations	7630	7656	7656	7471	7630
Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Adj.-R^2	0.068	0.033	0.083	0.263	0.101

Table 8: Illiquidity Discount on Capitalization Rate

This table shows regression results of the market liquidity on the individual capitalization rate (rent-to-price ratio). As proxies for market liquidity,I use the transaction volume (Column 1), the inventory share (Column 2), the turnover rate (Column 3), the average time on the market (Column 4), and the duration impact of trading volume (Column 5). I use lagged values of the market liquidity to avoid the endogeneity problem. The capitalization rate is based on a one-to-one matching algorithm of the rental offers with a dataset of 449,299 purchase offers of owner-occupied flats. I match rent with offer prices that are comparable in the hedonic characteristics. I control for all hedonic characteristics, local market conditions, and alternative investment opportunities (Swiss stock index return and government bond performance). The vector of confounding variables also include nonlinear effects (squared terms) and all possible interactions between the control variables that adds up to a vector with 308 variables. The estimates are based on several pre-selection techniques to reduce the dimensionality in the confounding factors. I apply the partialling out technique based on OLS and the Lasso estimator, the Double Selection using the Lasso to select important confounding factors, and the standard OLS model, including the baseline controls (a) and all interaction terms and nonlinear effects (b), respectively (see, e.g., Belloni, Chernozhukov, and Hansen (2014a), Belloni, Chernozhukov, and Hansen (2014b), Chernozhukov, Hansen, and Spindler (2015)). The adjusted R^2 is based on the baseline OLS model. The sample includes all municipalities within the labor market region of the five agglomeration centers Zurich, Geneva, Lausanne, Basel, and Bern in Switzerland. The sample ranges from 2004 to 2015. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Trading Volume	Inventory Share	Turnover Rate	Average Time on the Market	Duration Impact
Partialling Out OLS (a)	0.069***	0.047***	0.056***	-0.045***	-0.027***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
Partialling Out OLS (b)	0.055***	0.046***	0.055	-0.046***	-0.026***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
Partialling Out Lasso (b)	0.058***	0.046***	0.056***	-0.046***	-0.027***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
Double Selection Lasso (a)	0.068***	0.047***	0.056***	-0.045***	-0.025***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Baseline OLS(a)	0.069***	0.047***	0.056***	-0.045***	-0.027***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	286175	286175	286175	286175	286175
Adj.-R^2	0.063	0.091	0.095	0.084	0.095
Hedonic Controls	Yes	Yes	Yes	Yes	Yes
Market Controls	Yes	Yes	Yes	Yes	Yes
OCC Controls	Yes	Yes	Yes	Yes	Yes

This figure illustrates the descriptive survival function based on the Kaplan-Meier estimator. The horizontal axis indicates the duration (number of days) of the listed rent offers. The vertical axis reflects the share of rent offers (in percentage) that are on the market after a specific number of trading days. The slope of the hazard function is negative and monotonically decreasing. For instance, only 25% of all listed offers are on the market after 50 trading days.

Kaplan-Meier Survival Estimate
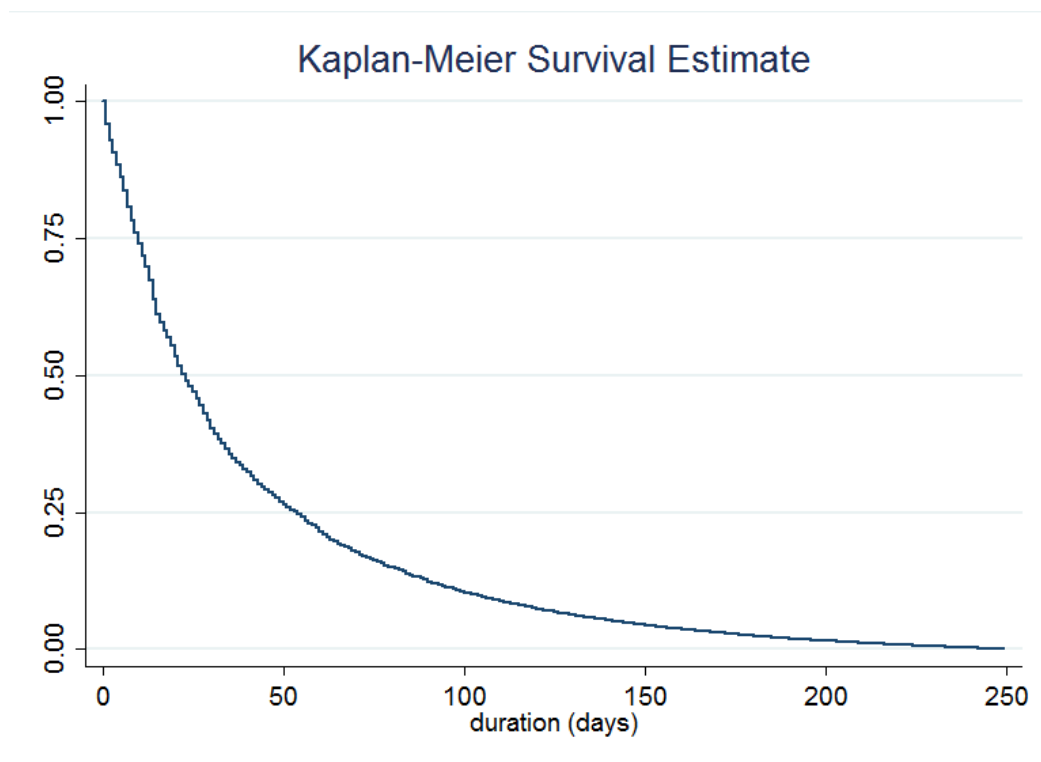
Figure 2: Cross-Sectional Distribution of Listed Rental Offers

This figure shows the cross-sectional distribution of the released rental offers in Switzerland. The trading activity is categorized according to the number of listed offers from 2004 to 2015 in local municipalities. The number of listings range from less than 10 (<10), to larger than 1600 (>1600). For some municipalities, no data is available. The figure also indicates the location (based on longitude and latitude) of the five largest agglomeration centers in Switzerland: Zurich, Geneva, Lausanne, Basel, Bern. The grey areas indicate municipalities with missing values.

Number of Listed Rent Offers in Swiss Housing Markets
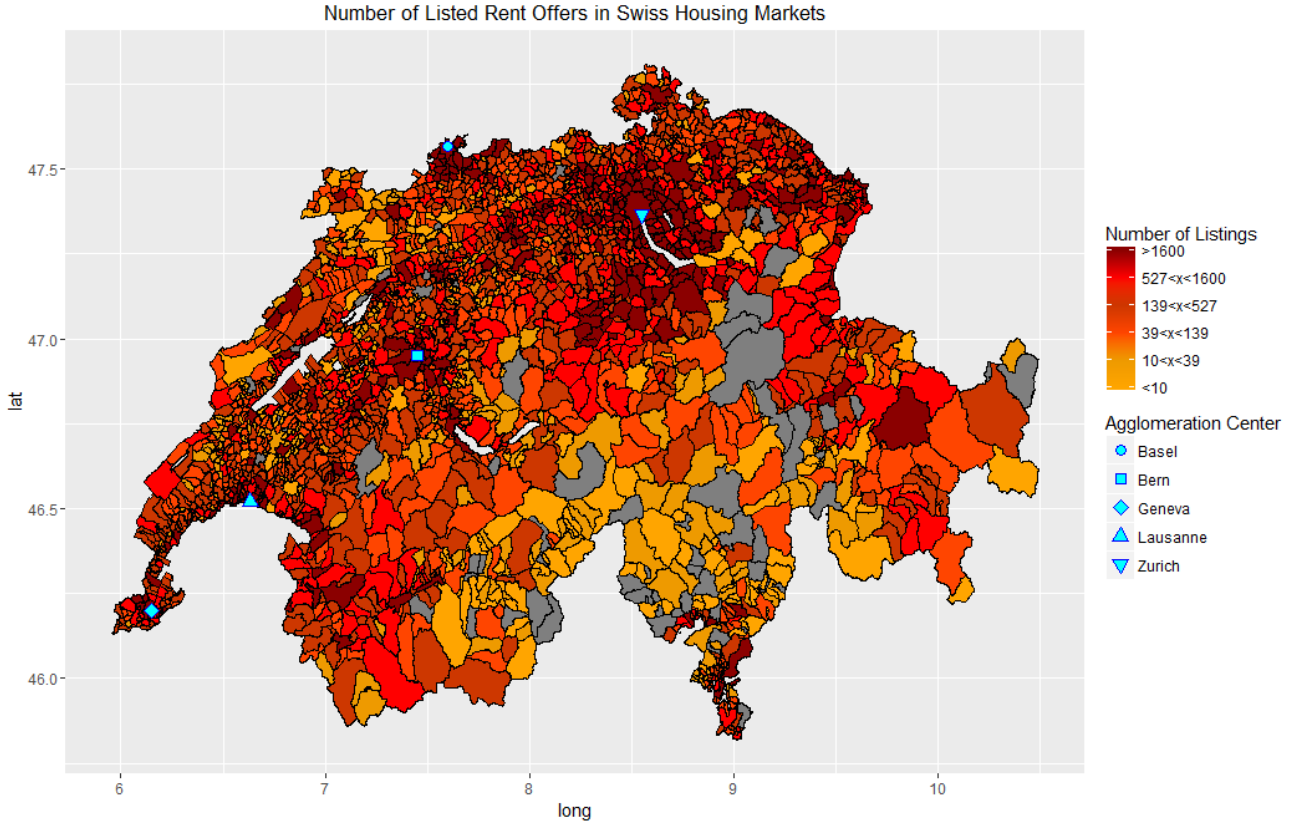
Figure 3: Market-wide Liquidity in Rental Housing Markets

This Figure illustrates the market-wide liquidity based on the five proxy variable. For each liquidity measure I rank the market-wide liquidity based on the quartiles of the geographic distance distribution from the urban center to the local market in the commuting area at its maximum distance from the center. The cut-off values are at the 25%, the median (50%), and the 75% of the distribution. The market-wide liquidity is computed as the cross-sectional average of the individual local market liquidity levels (Pastor and Stambaugh (2003)).
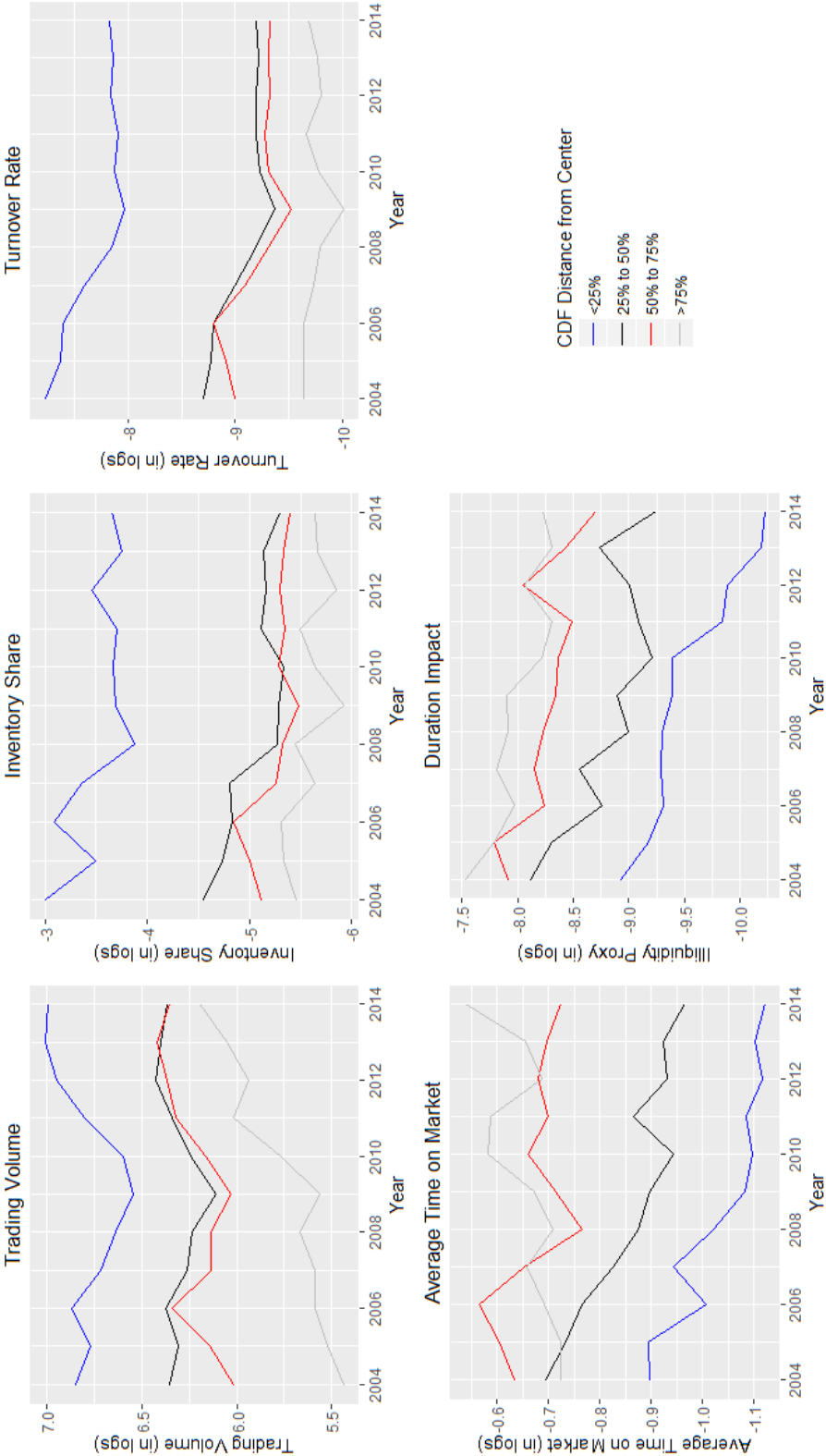
Internet Appendix for
"Agglomeration Effects and Liquidity Gradients in Local Rental Housing Markets"

Daniel Ruf *

January 30, 2017

Abstract

This supplementary appendix contains additional material related to the main paper. Appendix A discusses the construction of the Rental House Price Index and the Average Time on the Market. Appendix B and C provide a more detailed discussion about the identification strategy. Appendix D presents additional tables and figures.

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Appendix A: Construction of Rent Index

In this section, I describe the construction of the rent index for each municipality. To estimate the average rental price, I apply the hedonic regression approach. This estimation strategy accounts for the hedonic characteristics that influence the rent of the individual property, listed on the online market platform. First, I specify the steps for construction of the rental price index. Second, I provide a more detailed discussion about the hedonic attributes that are used in the regression.

Construction of the Rental Price Index: I follow a two-step approach to compute the hedonic house price index. In a first step, I estimate the fitted value of the renal price by using an OLS regression. The regression model follows a log-linear specification

$$log(R_{ijt}) = \beta_0 + \sum_{p=1}^{P} x_{i,j,p}\beta_p + \varepsilon_{ijt}, \tag{1}$$

with rental price R of the rental unit j, located in the municipality i, that exists the online search platform in period t. The rent is transformed to its natural logarithm. The set of P-dimensional housing attributes is denoted in levels. I assume that the value of the individual rental unit depends linearly on its unique bundle of hedonic characteristics (see, e.g., Rosen (1974)). The estimated parameters can be interpreted in terms of semi-elasticities and indicate the percentage change in the rental price following a unit change in the hedonic characteristics. Hence, the coefficients capture the sensitivity of the property-specific rent with respect to the priced hedonic factors. Table D.1 provides the regression results.

In a second step, I use the individual fitted rental values $\hat{R}_{ijt}$ to compute the cross-sectional local market-specific average of the rent level for each municipality and each period

$$\hat{R}_{it} = N^{-1}\sum_{j=1}^{n}\hat{R}_{ijt} \tag{2}$$

1

$$\hat{R}_{i,t-1} = N^{-1} \sum_{j=1}^{n} \hat{R}_{ij,t-1}. \tag{3}$$

Hedonic Variables: I use the following characteristics as priced factors of the rental unit.

Living Space and Number of Rooms: The main priced fundamental factors are the amount of living space, denominated in square meters, and the total number of rooms per rental unit.

Property-Specific Infrastructure: I include dummy variables that capture the architectural style of the unit (e.g., duplex, rooftop, studio, attica), whether the apartment is furnished, and whether the tenant has access to a balcony, a terrace, or a garden. I also capture building-specific infrastructure amenities, such as wheelchair access to the apartment and the existence of a lift.

Shared apartment: This dummy variable captures the required rental price discount if the potential tenant must share either the total apartment (e.g., living community) or parts of it, such as, sanitary facilities, laundry facilities, or the kitchen facility.

Minergie Certificate: The Minergie certificate is a Swiss label to evaluate the energy-efficiency of buildings. I use this dummy variable that equals 1 if the certificate exists for the rental unit to account for the sustainability-based price premium for the tenant as the property value is higher. For instance, Eichholtz and Quigley (2010) show empirical evidence of a rent premium for sustainability-labeled office properties in the USA.

Near Nature: This dummy variable equals to 1 if the rental unit is located in close distance to the nature, such as lakes or forest, or near mountain views, and captures local amenities. To construct this variables, I screen the posted descriptions of the listings and search for the following wordings: mountain(s), lake(s), forest(s). I assign the dummy variable equal to 1 if at least one of the selected words appear in the description of the released offer.

Seasonality: To account for potential seasonality, I follow Ngai and Tenreyro (2014).

They argue that realized transaction prices and trading activity follow a seasonal boom and bust pattern and systematically differ between hot (spring and summer) and cold (autumn and winter) seasons. I specify a dummy variable that equals 1 for the cold season (Quarter I and IV of the year). As rental prices are sticky, the sign of the coefficient is economically insignificant.

Appendix B: Propensity Score Approach with Continuous Treatment Variable

In the paper, I use three different propensity score approaches that are extended to the case of a continuous treatment. These empirical specifications serve as a robustness check to the baseline regression model and improve the comparability across the local markets. In this section, I briefly discuss each of the three techniques. Each approach is based on the underlying weak conditional independence assumption between a treatment variable T_i and the potential outcome of the endogenous variable $Y_i(t)$. Under the weak conditional independence assumption, $T_i \perp\!\!\!\perp Y_i(t)|X_i$, both variables are unrelated to each other conditional on a set of covariates. Standard empirical methods use the propensity score to adjust for systematic differences in the vector of covariates between the treated and the control group (see, e.g., Imbens and Wooldridge (2009)).

The first approach, as proposed by Hirano and Imbens (2004), is an extension of the standard propensity score model under a continuous treatment variable. The generalized propensity score is defined as the conditional distribution of the treatment variable $f(T_i|X_i)$ that can be used to adjust for systematic differences between the treated and the control group. The second approach is based on the parametric specification of the Covariate Balance Propensity Score (CBPS) as suggested by Fong, Hazlett, and Imai (2015). They also propose a non-parametric estimation strategy for the CBPS. This non-parametric version is the third approach that I use in the paper.[1]

Propensity Score Extension with Continuous Treatment: Imbens (2000) and Hirano and Imbens (2004) extend the standard propensity score approach with the potential outcome $Y_i(t)$ and vector of covariates $X_i(t)$ for a continuous treatment variable $T_i \in [t_0, t_1]$. They exploit the balancing property of the propensity score, i.e., the independence between the covariates and the realization of the treatment outcome conditional on the generalized propensity score, $X_i \perp\!\!\!\perp \mathbf{1}\{T_i = t\}|f(T_i = t|X_i)$. Together with the weak conditional independence assumption, the balancing property ensures that the

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[1] For more technical details, I refer the reader to the original work of Hirano and Imbens (2004) and Fong, Hazlett, and Imai (2015), respectively.

realization of the continuous treatment variable is independent on the potential outcome $Y(t)$ conditional on the propensity score, i.e., $Y_i(t)$, $T_i \perp\!\!\!\perp Y_i(t)|f(T_i = t|X_i)$.

I follow the estimation procedure of Hirano and Imbens (2004): In a first step, I estimate the following parametric specification $T_i = \beta_0 + X_i'\beta_1 + \varepsilon_i$ to compute the generalized propensity score based on the estimates for the parameter vector $\theta = (\beta_0, \beta_1, \sigma^2)$ from the vector X_i of control variables and the implied conditional normal density

$$f_\theta(T_i|_i) = \frac{1}{\sqrt{(2\pi\sigma^2)}}\left\{-\frac{1}{2\sigma^2}(T_i - \beta_0 - X_i'\beta_1)^2\right\}.$$

In a second step, I compute the conditional expectation of the endogenous variable as a linear parametric model of the treatment variable and the generalized propensity score $E(Y_i|T_i, f_\theta(T_i|X_i)) = \beta_0 + \beta_1 T_i + \beta_2 f_\theta(T_i|X_i)$.

In a third step, I compute the continuous response function $E(Y_i(t))$ as the cross-sectional average $N^{-1}\sum_{i=1}^{N}(\hat{\beta}_0 + \hat{\beta}_1 t_i + \hat{\beta}_2 f_\theta(t_i|X_i))$ at each level t_i of the treatment variable.

Covariate Balance Propensity Score (CBPS): Fong, Hazlett, and Imai (2015) extend the generalized CBPS approach of Imai and Ratkovic (2014) to a setting with a continuous treatment variable T_i. Imai and Ratkovic (2014) estimate the propensity score weights by directly exploiting the covariate balance property of the propensity score, i.e., the independence between the treatment variable and the vector of covariates that are weighted by the inverse propensity score. I briefly summarize the parametric and the non-parametric estimation procedure of the CBPS approach in the case of a continuous treatment variable.

Parametric Approach: In a first step, the treatment variable and the covariates are transformed by substracting the sample means, $T_i^\star = T_i - N^{-1}\sum_{i=1}^{N} T_i$ and $X_i^\star = X_i - N^{-1}\sum_{i=1}^{N} X_i$. As a consequence, the expected values of the transformed random variables are zero, $E(T_i^\star) = 0$ and $E(X_i^\star) = 0$. The balancing condition is given by the

moment condition

$$E\left(\frac{f(T_i^\star)}{f(T_i^\star|X_i^\star)}T_i^\star X_i^\star\right) = \int\left\{\int\frac{f(T_i^\star)}{f(T_i^\star|X_i^\star)}T_i^\star dF(T_i^\star|X_i^\star)\right\}X_i^\star dF(X_i^\star) = E(T_i^\star)E(X_i^\star) = 0,$$

with the chosen weights $\frac{f(T_i^\star)}{f(T_i^\star|X_i^\star)}$ to minimize the weighted correlation between $T_i^\star$ and $X_i^\star$. Based on the underlying model assumption, the generalized propensity score follows a conditional normal density

$$f(T_i^\star|X_i^\star) = \frac{1}{\sqrt{2\pi\sigma^2}}exp\left\{-\frac{1}{2\sigma^2}(T_i^\star - X_i^{\star'}\beta)^2\right\}$$

and the balancing weights are given by

$$\frac{f(T_i^\star)}{f(T_i^\star|X_i^\star)} = exp\left[\frac{1}{2\sigma^2}\left\{-2T_i^\star X_i^{\star'}\beta + (X_i^{\star'}\beta)^2\right\}\right].$$

In a second step, I specify the propensity score weights. Therefore, I apply GMM to estimate the parameter vector $\theta = (\beta, \sigma^2)$ based the following minimization problem

$$\hat{\theta}_{CBPS} = argmin_\theta \bar{g}_\theta(T_i, X_i)'\Sigma_\theta(T_i, X_i)^{-1}\bar{g}_\theta(T_i, X_i)$$

with the sample moment condition $\bar{g}_\theta(T_i, X_i) = N^{-1}\sum_{i=1}^{N} g_\theta(T_i, X_i)$ and the sample co-variance matrix $\Sigma_\theta(T_i, X_i)$.

Fong, Hazlett, and Imai (2015) define the sample moment condition as

$$g_\theta(T_i, X_i) = \begin{pmatrix} s_\theta(T_i^\star, X_i^\star) \\ w_\theta(T_i^\star, X_i^\star) \end{pmatrix} = \begin{pmatrix} \frac{1}{\sigma^2}(T_i^\star - X_i^{\star'}\beta)X_i^{\star'}\beta \\ -\frac{1}{2\sigma^2}\left\{1 - \frac{1}{\sigma^2}(T_i^\star - X_i^{\star'}\beta)^2\right\} \\ exp\left[\frac{1}{2\sigma^2}\left\{-2T_i^\star X_i^{\star'}\beta + (X_i^{\star'}\beta)^2\right\}\right]T_i^\star X_i^\star \end{pmatrix},$$

where they use the score and balancing moment conditions, $s_\theta(T_i^\star, X_i^\star)$ and $w_\theta(T_i^\star, X_i^\star)$,

respectively. They also derive the corresponding covariance matrix

$$\Sigma_\theta(T_i, X_i) = \frac{1}{N} \sum_{i=1}^{N} \begin{pmatrix} \frac{1}{\sigma^2} X_i^\star X_i^{\star'} & 0 & X_i^\star X_i^{\star'} \\ 0 & \frac{1}{2\sigma^4} & -\frac{X_i^\star \beta}{\sigma^2} X_i^{\star'} \\ X_i^\star X_i^{\star'} & -\frac{X_i^\star \beta}{\sigma^2} X_i^\star & exp\left(\frac{(X_i^\star \beta)^2}{\sigma^2}\right)\left\{\sigma^2 + (X_i^\star \beta)^2\right\} X_i^\star - X_i^{\star'} \end{pmatrix}.$$

The relevant proofs and more technical details can be found in their paper.

Non-Parametric Approach: Fong, Hazlett, and Imai (2015) also provide a non-parametric estimation strategy to overcome the limitation of specifying a restrictive functional form for the generalized propensity score. I briefly discuss this non-parametric estimation strategy.

Similar to the parametric specification, the continuous treatment variable and the K-dimensional vector of covariates are normalized, i.e., $\tilde{X}_i = S_X^{-1/2}(X_i - \bar{X})$ and $\tilde{T}_i = S_T^{-1/2}(T_i - \bar{T})$, using their respective sample means and sample covariance. The weightings are defined as $w_i = \frac{f(\tilde{T}_i)}{f(\tilde{T}_i)|\tilde{X}_i}$. The covariate balancing condition is defined as

$$E(w_i \tilde{X}_i \tilde{T}_i) = \int_{\tilde{X}_i} \int_{\tilde{T}_i} \frac{f(\tilde{T}_i)}{f(\tilde{T}_i)|\tilde{X}_i} \tilde{X}_i \tilde{T}_i f(\tilde{T}_i|\tilde{X}_i) f(\tilde{x}_i) d\tilde{X}_i d\tilde{T}_i = E(\tilde{X}_i)E(\tilde{T}_i) = 0,$$

from which the additional sample constraints $\sum_{i=1}^{N} w_i g(\tilde{X}_i \tilde{T}_i) = 0$ and $\sum_{i=1}^{N} w_i - N = 0$, with $g(\tilde{X}_i \tilde{T}_i) = [\tilde{X}_i' \tilde{T}_i, \tilde{X}_i \tilde{T}_i]'$, are derived. As implied by parameter ρ in the prior distribution of the sample correlation $\frac{1}{N} \sum_{i=1}^{N} w_i \tilde{X}_i \tilde{T}_i \sim \mathcal{N}(0, \rho I_K)$, the model allows for possible correlation between the treatment and the covariates. The tuning parameter ρ is set to the value 0.1 and the weightings are calculated by the following optimization process:

$$argmin_{w \in \mathbb{R}^K, \eta \in \mathbb{R}^K} \left[\sum_{i=1}^{n} log(w_i) + \frac{1}{2\rho} \eta^\top \eta \right]$$

subject to the following constraints $\sum_{i=1}^{N} w_i g(\tilde{X}_i \tilde{T}_i) = \eta$ and $\sum_{i=1}^{N} w_i - N = 0$.

Appendix C: Pre-Selection Techniques for High-Dimensional Controls

In section 5.4 of the paper, I estimate a model specification with a high-dimensional vector of controls X_i. Based on the conditional independence assumption I allow for quadratic terms and potential interaction effects between the control variables to mitigate the potential endogeneity between the endogenous variable Y_i and the explanatory variable of interest T_i. However, this flexible functional form specification increases the number of estimated parameters. Therefore, I apply empirical techniques for pre-selection of relevant confounding factors from a big data set with many potential control variables. In this section, I briefly discuss each chosen approach.

Variable Selection and Omitted-Variables Bias: In a first step, I discuss how an additional auxiliary regression between the treatment variable and the set of control variables is used for the pre-selection of confounding factors that are highly correlated with the treatment variable. Each chosen empirical method is based on this auxiliary reduced-form specification between the explanatory variable T_i and the vector of controls X_i. The conditional independence assumption is based on a set of confounding factors that jointly influence the endogenous variable Y_i and the treatment variable T_i. The pre-selection of the relevant control variables is based on their prediction quality in the reduced-form model and allows to mitigate the omitted-variables bias (Belloni, Chernozhukov, and Hansen (2014a)).

Pre-Selection Techniques: The following section focuses on the different pre-selection techniques. I briefly describe the estimation steps for each of the chosen methods.

Partialling Out based on OLS: Consider the following the linear structural model

$$Y_i = \beta T_i + X_i^{'}\delta + \varepsilon_i^y$$

with treatment variable T_i conditional on the vector of controls X_i and $E(\varepsilon_i|T_i, X_i) = 0$. I also specify a linear reduced-form model between the treatment variable and the vector

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of controls

$$T_i = X_i^{'} \gamma + \varepsilon_i^t$$

To reduce the dimensionality in the structural model, I follow the two-step approach, proposed by empirical studies, such as Chernozhukov, Hansen, and Spindler (2015). I first compute the residuals $\hat{\varepsilon}_i^y$ and $\hat{\varepsilon}_i^t$ from the corresponding linear projections on the P-dimensional control vector X_i. The corresponding coefficient vectors γ_1 and γ_2 are based on the mean squared error (MSE) minimizing least squares, i.e., $\hat{\gamma_1} = argminE(Y_i - \sum_{p=1}^{P} x_{i,p}\gamma_{p,1})^2$ and $\hat{\gamma_2} = argminE(T_i - \sum_{p=1}^{P} x_{i,p}\gamma_{p,2})^2$, respectively. Second, I regress the residuals $\hat{\varepsilon}_i^y$ on $\hat{\varepsilon}_i^t$ to partial-out the effect of the high-dimensional control vector X_i. Following the Frisch-Waugh-Lovell-theorem, parameter β can be recovered from the simple regression model with the residual components $\hat{\varepsilon}_i^y$ and $\hat{\varepsilon}_i^t$, only.

Partialling Out based on Lasso: I also apply the partialling-out approach based on the least absolute shrinkage and selection operator (Lasso) (see, e.g., Tibshirani (1996)). Using the Lasso-estimator instead of OLS allows to pre-select only the relevant confounding variables in the first step that are highly correlated with the treatment and the endogenous variable. Following Belloni, Chen, Chernozhukov, and Hansen (2012), I apply the following optimization $\gamma_{lasso,1} = argminE(Y_i - \sum_{p=1}^{P} x_{i,p}\gamma_{p,1})^2 + \lambda \sum_{p=1}^{P} | b_p | \omega_{jp}$ and $\gamma_{lasso,2} = argminE(T_i - \sum_{p=1}^{P} x_{i,p}\gamma_{p,1})^2 + \lambda \sum_{p=1}^{P} | b_p | \omega_{jp}$, respectively. The tuning parameter λ and the penalty loadings ω_j are chosen based on a data-driven approach.

Double Selection based on Lasso: The third approach is based on a double selection method as suggested by Belloni, Chernozhukov, and Hansen (2014b): First, I pre-select all controls that are either highly correlated with the endogenous variable or have a high prediction power for the treatment. In both cases, I apply the Lasso for pre-selection. In a second step, I regress the endogenous variable on the treatment variable and the P-dimensional vector of confounding factors. The Post-Lasso estimates are estimated by $(\hat{\alpha}, \hat{\beta}) = argminE(Y_i - T_i\alpha - \sum_{p=1}^{P} x_{ip}\beta_p)^2$, with the parameter restrictions $\beta_p = 0$ for the corresponding first-step Lasso-estimates with zero restriction.

Appendix D: Additional Tables and Figures

In this part of the appendix I provide additional figures tables that extend the empirical analysis in the paper.

- Table D.1 provides the hedonic regressions for the rental offer prices and the duration on the market, respectively.

- Table D.2 tests the baseline regression model for a nonlinear effect of distance.

- Table D.3 shows the empirical evidence of the liquidity gradient conditional on a set of further covariates. Particularly, I include market conditions at the state-level, geographical and locational characteristics of the local markets.

- Table D.4 provides additional robustness of the effect of urban agglomeration externalities on local markets. I show the effect of a negative urban externality.

- Table D.5 replicates the baseline regressions with the rent level as endogenous variable to support the rent gradient hypothesis.

- Table D.6 provides empirical evidence of spillover effect from the local market liquidity of the urban agglomeration center on the liquidity of nearby located municipalities within the commuting area.

- Table D.7 shows the relation between individual property-specific capitalization rates and the local market liquidity conditional on hedonic characteristics, alternative investment opportunities, and the local economic market condition.

- Figure D.1 provides an overview of the municipalities that are located within the labor market regions of the five urban agglomeration centers in Switzerland. The empirical analysis is based on a pooled dataset that only included these municipalities as local markets.

- Figure D.2 shows the Box-Whisker plots for the cross-sectional distribution of the local liquidity measures based on the distance distribution from the urban agglomeration center.

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Table D.1: Hedonic Regression

This table provides the results of the hedonic regressions for the offer prices and the duration. Both endogenous variables are denoted in their levels. The sample ranges from 2004 to 2015 and includes all listed rent offers from online search platforms in Switzerland. Standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	log(offer price)	log(duration)
Living surface	0.006***	0.002**
	(0.000)	(0.000)
Rooms	0.079***	0.123***
	(0.000)	(0.002)
Minergie certificate	0.105***	0.195***
	(0.002)	(0.007)
Balcony	0.027***	-0.006***
	(0.0005)	(0.002)
Terrace	0.090***	-0.017***
	(0.001)	(0.003)
Garden	0.033***	-0.067***
	(0.001)	(0.003)
Shared apartment	-0.280***	0.061**
	(0.006)	(0.028)
Near nature	0.105***	-0.131***
	(0.001)	(0.003)
Duplex	0.009***	0.044***
	(0.001)	(0.005)
Rooftop	0.001	0.105***
	(0.001)	(0.005)
Attica	0.109***	0.202***
	(0.001)	(0.006)
Studio	-0.131***	0.164***
	(0.002)	(0.009)
Loft	0.131***	0.184***
	(0.002)	(0.010)
Furnished	0.185***	0.091***
	(0.001)	(0.005)
Wheelchair access	0.035***	0.107***
	(0.001)	(0.004)
Lift	0.089***	0.037***
	(0.001)	(0.002)
Seasonality	-0.001***	0.009***
	(0.000)	(0.001)
Observations	1610047	1670611
Adj.-R^2	0.595	0.031

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Table D.2: Liquidity Gradient with Nonlinear Effects

This Table shows the regression results of the liquidity gradient for the different local liquidity measures: trading volume (Column 1), the inventory share (Column 2), the turnover rate (Column 3), the average time on the market (Column 4), and the duration impact of trading volume (Column 5). The geographic distance is computed as the Haversine distance measured in kilometers to capture the shape of the earth. Distance is specified as a nonlinear effect, including the squared distance. The covariates include the average rent level, the vacancy rate, population growth (Δ Population), the share of land supply restrictions (Undevelopable Land), the annual growth of commuters to the local market (Δ Commuter), and the annual percentage of private and public investments in the local infrastructure (Δ Infrastructure). All covariates are used at the lagged value to avoid the endogeneity problem. The sample includes all municipalities within the labor market region of the five largest agglomeration centers in Switzerland (Zurich, Geneva, Basel, Lausanne, Bern). The definition of the labor market region follows the Swiss Statistical office. Liquidity is measured for each municipality from 2004 to 2015. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	Trading Volume	Inventory Share	Turnover Rate	Average Time on the Market	Duration Impact
Distance	-0.021	-0.032**	-0.019	0.006	0.029
	(0.015)	(0.014)	(0.014)	(0.011)	(0.023)
Distance^2	-0.000	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Rent)	0.554***	-0.652***	-0.670***	0.831***	1.089***
	(0.106)	(0.142)	(0.140)	(0.115)	(0.244)
Vacancy Rate	3.326***	2.404***	2.466***	0.996***	-1.370*
	(0.288)	(0.471)	(0.460)	(0.349)	(0.807)
Δ Population	6.828***	3.195***	3.132***	2.589***	-1.892
	(0.888)	(1.127)	(1.040)	(0.865)	(1.798)
Undevelopable Land	1.730***	5.034***	5.016***	-3.565***	-8.759***
	(0.299)	(0.381)	(0.374)	(0.321)	(0.655)
Δ Commuter	0.133***	0.249***	0.245***	-0.104***	-0.352***
	(0.028)	(0.055)	(0.045)	(0.036)	(0.077)
Δ Infrastructure	0.074***	0.055***	0.043***	0.030***	-0.034
	(0.013)	(0.020)	(0.016)	(0.011)	(0.027)
Observations	8605	8632	8632	8434	8605
Year dummies	Yes	Yes	Yes	Yes	Yes
Adj.-R^2	0.280	0.367	0.410	0.318	0.375

Table D.3: Liquidity Gradient: Robustness with Additional Covariates

This table provides additional evidence of the liquidity gradient hypothesis for the different liquidity measures: Trading volume, the inventory share, the turnover rate, the average time on the market, and the duration impact of trading volume. In addition to the set of market conditions of the baseline model I include Canton dummies (specification a), canton-specific unemployment rate and the taxation of the median income of CHF 50,000 (specification b), location dummies (specification c), and Municipality-based dummies (specification d). Locational dummies include regions in the Jura mountains, the Swiss Alps, and the regions with French as local language. Municipality-based dummies include whether a local market belongs to the commuting area of another agglomeration area, belongs to a rural area, or is an isolated municipality. The sample ranges from 2004 to 2015. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Trading Volume				Inventory Share			
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
Distance	-0.031***	-0.024***	-0.015***	-0.011***	-0.034***	-0.027***	-0.031***	-0.015***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)	(0.006)	(0.005)
log(Rent)	0.398***	0.468***	0.471***	0.564***	-0.597***	-0.605***	-0.468***	-0.634***
	(0.095)	(0.104)	(0.106)	(0.098)	(0.129)	(0.135)	(0.144)	(0.133)
Vacancy Rate	2.912***	2.913***	3.126***	2.970***	1.450***	1.731***	1.700***	2.227***
	(0.277)	(0.270)	(0.286)	(0.271)	(0.421)	(0.455)	(0.454)	(0.421)
Δ Population	3.794***	6.360***	5.974***	6.207***	3.169***	3.693***	4.981***	2.311**
	(0.715)	(0.831)	(0.802)	(0.826)	(1.027)	(1.101)	(1.110)	(1.074)
Undevelopable Land	1.557***	1.463***	1.637***	0.851***	4.881***	4.992***	4.939***	3.710***
	(0.232)	(0.266)	(0.304)	(0.269)	(0.344)	(0.352)	(0.376)	(0.329)
Δ Commuter	0.055**	0.109***	0.119***	0.094***	0.171***	0.235***	0.223***	0.153***
	(0.025)	(0.028)	(0.029)	(0.025)	(0.046)	(0.053)	(0.051)	(0.048)
Δ Infrastructure	0.053***	0.072***	0.068***	0.070***	0.059***	0.058***	0.071***	0.052***
	(0.011)	(0.013)	(0.013)	(0.013)	(0.019)	(0.019)	(0.020)	(0.019)
Δ Unemployment		-0.124**				-0.090		
		(0.049)				(0.076)		
$Tax_{married,0child.}$		-0.0003***				-0.0003***		
		(0.000)				(0.000)		
$Tax_{married,2child.}$		0.001***				0.001***		
		(0.000)				(0.000)		
$Tax_{single,2child.}$		-0.001***				0.0000		
		(0.000)				(0.000)		
$Language_{french}$			-0.074				-0.635***	
			(0.074)				(0.106)	
Observations	8605	8605	8605	8605	8632	8632	8632	8632
Canton FE	Yes	No	No	No	Yes	No	No	No
Year FE	Yes	No	No	No	Yes	No	No	No
Location Controls	No	No	Yes	No	No	No	Yes	No
Municipality Controls	No	No	No	Yes	No	No	No	Yes
Adj.-R^2	0.453	0.324	0.315	0.361	0.451	0.385	0.390	0.431

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Table D.3 continued.

	Turnover Share				Average Time on the Market				Duration Impact			
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
Distance	-0.030***	-0.024***	-0.025***	-0.010**	0.007	0.007*	0.017***	0.005	0.041***	0.036***	0.015***	0.017**
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)	(0.008)	(0.004)	(0.008)
log(Rent)	-0.567***	-0.607***	-0.486***	-0.650***	0.660***	0.721***	0.516***	0.718***	0.852***	0.955***	0.471***	0.867***
	(0.124)	(0.133)	(0.141)	(0.128)	(0.108)	(0.109)	(0.114)	(0.104)	(0.219)	(0.323)	(0.106)	(0.220)
Vacancy Rate	1.481***	1.766***	1.828***	2.289***	1.527***	1.310***	1.561***	1.004***	0.099	-0.312	3.126***	-0.935
	(0.403)	(0.435)	(0.441)	(0.404)	(0.336)	(0.341)	(0.333)	(0.322)	(0.718)	(0.763)	(0.286)	(0.682)
Δ Population	2.759***	3.541***	4.865***	2.262**	0.406	2.213***	-0.111	2.546***	-3.145**	-2.102	5.974***	-1.282
	(0.902)	(1.012)	(1.007)	(0.972)	(0.715)	(0.842)	(0.749)	(0.825)	(1.567)	(1.767)	(0.802)	(1.691)
Undevelopable Land	4.915***	4.914***	4.922***	3.578***	-3.518***	-3.577***	-3.411***	-2.855***	-8.589***	-8.510***	1.637***	-6.298***
	(0.335)	(0.345)	(0.374)	(0.325)	(0.295)	(0.304)	(0.311)	(0.275)	(0.599)	(0.610)	(0.304)	(0.554)
Δ Commuter	0.161***	0.230***	0.218***	0.150***	-0.080***	-0.134***	-0.141***	-0.098***	-0.227***	-0.390***	0.119***	-0.299***
	(0.036)	(0.044)	(0.041)	(0.038)	(0.028)	(0.036)	(0.032)	(0.032)	(0.062)	(0.077)	(0.029)	(0.067)
Δ Infrastructure	0.044***	0.045***	0.057***	0.039***	0.013	0.030***	0.013	0.031***	-0.048*	-0.033	0.068***	-0.029
	(0.015)	(0.016)	(0.016)	(0.015)	(0.011)	(0.012)	(0.010)	(0.011)	(0.025)	(0.026)	(0.013)	(0.025)
Δ Unemployment		-0.081				-0.140***				-0.200**		
		(0.058)				(0.037)				(0.101)		
Tax$_{married,0child.}$		-0.0002**				-0.000				0.000		
		(0.000)				(0.000)				(0.000)		
Tax$_{married,2child.}$		0.001***				-0.0002***				-0.001***		
		(0.0001)				(0.000)				(0.000)		
Tax$_{single,2child.}$		-0.0001				0.0001				0.001***		
		(0.0001)				(0.000)				(0.000)		
Language$_{french}$			-0.623***				0.537***				-0.074	
			(0.103)				(0.084)				(0.074)	
Observations	8632	8632	8632	8632	8434	8434	8434	9434	8605	8605	8605	8605
Canton FE	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No
Year FE	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No
Location Controls	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No
Municipality Controls	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Adj.-R^2	0.515	0.431	0.432	0.491	0.435	0.319	0.412	0.386	0.478	0.382	0.315	0.458

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Table D.4: Negative Agglomeration Externalities

This table shows regression results of the effect of the amount of burglary per 1000 residents in the urban center on the following liquidity measures: trading volume (Column 1), the inventory share (Column 2), the turnover rate (Column 3), the average time on the market (Column 4), and the duration impact of trading volume (Column 5). The sample ranges from 2011 to 2014. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Trading Volume	Inventory Share	Turnover Rate	Average Time on the Market	Duration Impact
Distance	-0.052***	-0.070***	-0.060***	0.013	0.079***
	(0.010)	(0.018)	(0.016)	(0.013)	(0.028)
Burglary	-0.135***	-0.134**	-0.141***	0.016	0.188**
	(0.040)	(0.058)	(0.051)	(0.042)	(0.091)
Burglary $\times Distance$	0.004**	0.006**	0.005**	-0.001	-0.006*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
log(Rent)	0.519***	-0.464*	-0.505**	0.705***	0.750*
	(0.194)	(0.258)	(0.248)	(0.216)	(0.448)
Vacancy Rate	2.817***	0.883	0.895	1.933***	1.227
	(0.444)	(0.758)	(0.652)	(0.552)	(1.199)
Δ Population	4.328***	4.361**	4.525***	-0.747	-5.824*
	(1.436)	(1.926)	(1.654)	(1.443)	(2.981)
Undevelopable Land	1.583***	5.241***	5.172***	-3.837***	-9.291***
	(0.363)	(0.541)	(0.511)	(0.465)	(0.923)
Δ Commuter	0.041	0.118	0.140*	-0.073	-0.224*
	(0.062)	(0.088)	(0.074)	(0.050)	(0.123)
Δ Infrastructure	0.060**	0.069	0.048	0.019	-0.053
	(0.194)	(0.047)	(0.040)	(0.026)	(0.064)
Observations	3666	3674	3674	3622	3666
Canton Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Adj.-R^2	0.453	0.458	0.513	0.461	0.492

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Table D.5: Rent Gradient and Agglomeration Externalities

This table replicates the regression results for the rent level (in logs). Model (1) regresses the market-specific rent on the distance to the urban agglomeration center to test the rent gradient hypothesis. Models (2) and (3) show the impact of agglomeration externalities on the local rent level. The sample ranges from 2004 to 2014. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
Distance	-0.002***	-0.001	-0.003**
	(0.0004)	(0.001)	(0.002)
Site Quality Index (SQI)		0.044**	
		(0.017)	
SQI $\times Distance$		-0.001*	
		(0.001)	
Burglary			-0.018**
			(0.007)
Burglary $\times distance$			0.0001
			(0.000)
Vacancy Rate	-0.138***	-0.070	0.036
	(0.043)	(0.044)	(0.067)
Δ Population	0.852***	0.438**	0.050
	(0.163)	(0.172)	(0.352)
Undevelopable Land	-0.177***	-0.254***	-0.189***
	(0.034)	(0.033)	(0.055)
Δ Commuter	0.004	-0.003	-0.003
	(0.007)	(0.007)	(0.014)
Δ Infrastructure	0.005	0.002	-0.0000
	(0.003)	(0.004)	(0.009)
Observations	9800	8837	3790
Canton Fixed-Effects	No	Yes	Yes
Adj.-R^2	0.031	0.115	0.171

Table D.6: Spillover effects

This table shows the effect of local liquidity in the urban center on the rental market liquidity in local municipalities that are included in the urban labor market region around the agglomeration center. I use the lagged value of the liquidity in the urban center liquidity to avoid the endogeneity problem. The endogenous variables are the trading volume (Column 1), the inventory share (Column 2), the turnover rate (Column 3), the average time on the market (Column 4), and the duration impact of trading volume (Column 5), respectively. The local market liquidity proxies are computed for the municipalities that are included in the labor market region around the local agglomeration center. The market liquidity of the urban center is excluded from the panel data of endogenous variables. The sample ranges from 2011 to 2014. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Trading Volume	Inventory Share	Turnover Rate	Average Time on the Market	Duration Impact
$\text{Liquidity}_{center,t-1}$	-0.034	0.012	0.211***	0.249***	0.172***
	(0.031)	(0.017)	(0.031)	(0.010)	(0.013)
Vacancy Rate	0.738***	0.569**	0.443***	0.260***	-0.034
	(0.161)	(0.231)	(0.137)	(0.058)	(0.159)
Δ Unemployment	-0.239***	-0.137**	-0.021	-0.003	0.099*
	(0.037)	(0.060)	(0.033)	(0.013)	(0.057)
Δ Population	0.330	0.767	0.460	-0.163	-0.839**
	(0.408)	(0.556)	(0.358)	(0.107)	(0.422)
Δ Infrastructure	0.026***	0.029**	0.020**	0.002	-0.022**
	(0.008)	(0.011)	(0.008)	(0.002)	(0.009)
Short-Term Interest	-0.095***	-0.048***	-0.057***	0.003*	0.110***
	(0.006)	(0.008)	(0.006)	(0.002)	(0.007)
Δ Commuter	-0.021	-0.008	0.000	-0.001	0.001
	(0.018)	(0.030)	(0.016)	(0.006)	(0.024)
Δ Migration	-1.185	-11.971***	-8.606***	-2.652***	-11.63***
	(0.966)	(1.266)	(0.956)	(0.269)	(1.004)
Observations	9384	9437	9437	9037	9384
Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Adj.-R^2	0.070	0.029	0.072	0.360	0.126

Table D.7: Illiquidity Discount on Capitalization Rate

This table shows regression results of the market liquidity on the individual capitalization rate (rent-to-price ratio). As proxies for liquidity, I use the transaction volume (Column 1), the inventory share (Column 2), the turnover rate (Column 3), the average time on the market (Column 4), and the duration impact of trading volume (Column 5). I use lagged values of the market liquidity to avoid the endogeneity problem. The capitalization rate is based on a one-to-one matching algorithm of the rental offers with a dataset of 449,299 purchase offers of owner-occupied flats. I match rent with offer prices that are comparable in the hedonic characteristics. I control for all hedonic characteristics, local market conditions, and alternative investment opportunities (Swiss stock index return and government bond performance). The sample includes all municipalities within the labor market region of the five agglomeration centers Zurich, Geneva, Lausanne, Basel, and Bern in Switzerland. The sample ranges from 2004 to 2015. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Trading Volume	Inventory Share	Turnover Rate	Average Time on the Market	Duration Impact
Liquidity	0.069***	0.047***	0.056***	-0.045***	-0.027***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
Vacancy Rate	-0.583***	-0.013	0.005	0.099***	0.097***
	(0.022)	(0.020)	(0.020)	(0.021)	(0.205)
Δ Unemployment	0.095***	0.092***	0.084***	0.082***	0.070***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Δ Population	-1.092***	-0.786***	-0.754***	-0.743***	-0.702***
	(0.103)	(0.101)	(0.101)	(0.102)	(0.101)
Δ Infrastructure	-0.012***	-0.008***	-0.008**	-0.011***	-0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Δ Commuter	-0.018***	0.023***	0.021***	0.030***	0.024***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Undevelopable Land	0.015	-0.308***	-0.307***	-0.317***	-0.319***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.030)
Δ GDP	0.386***	0.402***	0.329**	0.347***	0.272**
	(0.130)	(0.128)	(0.129)	(0.130)	(0.128)
Δ Stock	0.118***	0.172***	0.135***	0.347***	0.097***
	(0.019)	(0.018)	(0.018)	(0.130)	(0.018)
Term Spread	1.989*	1.168	2.846***	3.879***	3.641***
	(1.111)	(1.087)	(1.086)	(1.094)	(1.086)
Δ CPI	-3.563***	-4.018***	-2.407**	-0.456	-0.944
	(1.087)	(1.067)	(1.065)	(1.073)	(1.066)
Observations	286150	286187	286187	286021	286150
Hedonic Controls	Yes	Yes	Yes	Yes	Yes
Adj.-R^2	0.063	0.091	0.095	0.084	0.095

Figure C.1: Labor Market Regions around the Urban Agglomeration Centers

This figure illustrates the labor market regions that surround the five agglomeration centers in Switzerland. I use all local municipalities that are located within the labor market region in the pooled dataset for the further empirical analysis. The classification of municipalities within the labor market region around the urban centers follows the definition of the Federal Statistical Office.
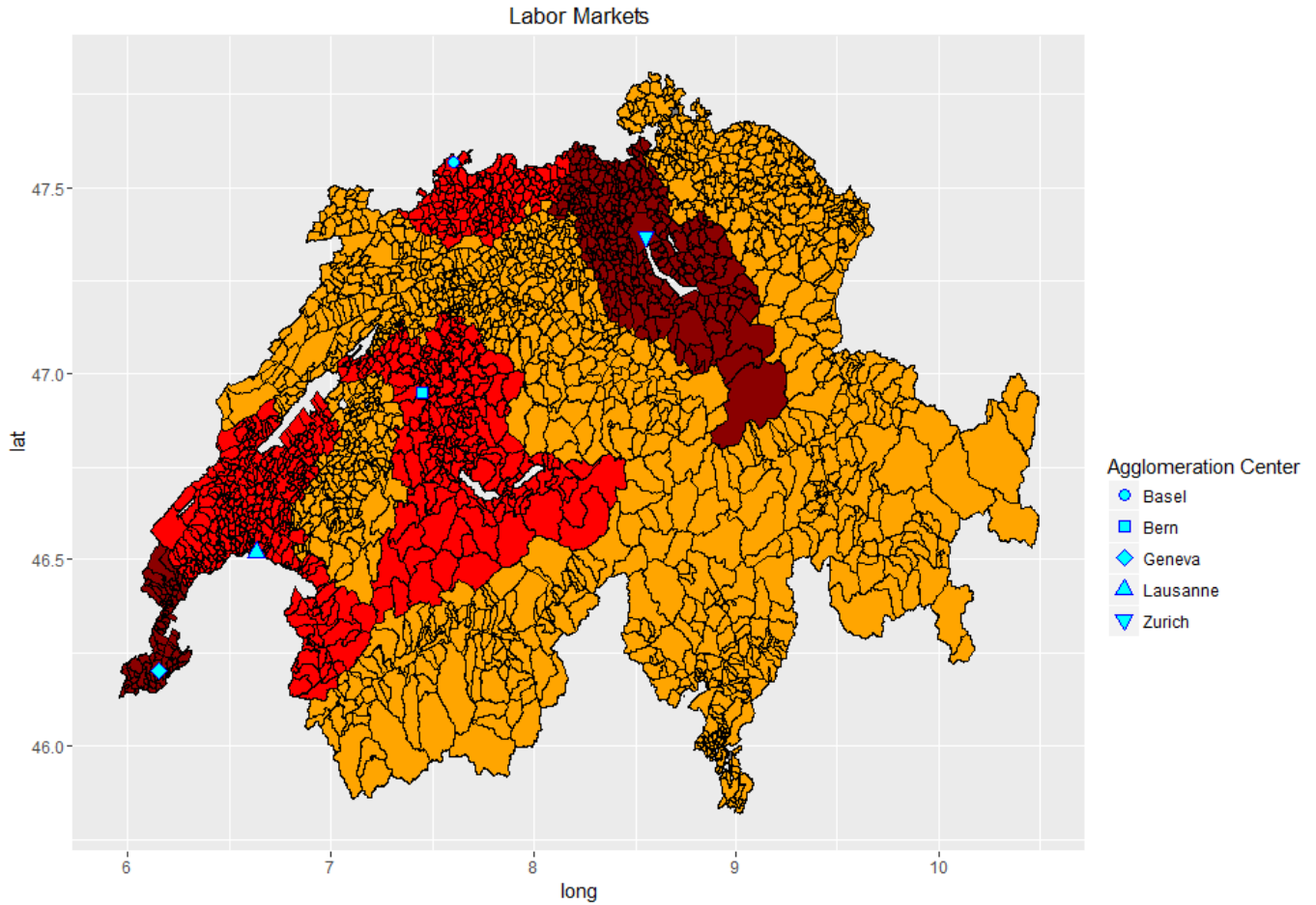
Figure C.2: Cross-Sectional Distribution of Local Liquidity

This figure provides the Box-Whiskers plots for each of the local liquidity measures: the trading volume, the inventory share, the turnover rate, the average time on the market, and the duration impact of trading volume. Local liquidity is categorized according to the 10%-quantiles of the distance distribution from the urban agglomeration center. The solid black line denotes the median within the range of the 25%- and the 75%-quantiles. The dashed lines capture the interquartile range $(Q_{0.75} - Q_{0.25})$ times 1.5.