School of Finance

University of St.Gallen

# AGGLOMERATION EFFECTS AND LIQUIDITY GRADIENTS IN LOCAL RENTAL HOUSING MARKETS

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WORKING PAPERS ON FINANCE NO. 2016/23

SWISS INSTITUTE OF BANKING AND FINANCE (S/BF – HSG)

NOVEMBER 2016

# Agglomeration Effects and Liquidity Gradients in Local Rental Housing Markets*

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November 16, 2016

**Abstract**

This paper empirically analyzes the relation between local liquidity in rental housing markets and urban agglomeration effects. Using listed rent offers from online market platforms, I study the cross-sectional variation of rental market liquidity. Local liquidity is negatively related to the distance to nearby located urban agglomeration centers, manifesting in a decreasing liquidity gradient. I show that agglomeration externalities expose local rental markets to a systematic liquidity risk. Furthermore, more thinly traded rental markets offer lower capitalization rates for investors.

**JEL Classification:** $G12$, $R31$, $R40$
**Key words:** Urban agglomeration effects; Liquidity; Rental housing market.

*Acknowledgement: For helpful comments, I am indebted to Zeno Adams, Martin Brown, Falko Fecht, Roland Füss, Thomas Gehrig, the participants at the Brown Bag Seminar of the School of Finance, University of St.Gallen, and the Bundesbank Project Group on "Big Data". I am grateful to Daniel Sager for providing the data.

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# 1 Introduction

Does liquidity in rental housing markets depend on urban agglomeration externalities? Do local rental markets that are more distant from agglomeration centers suffer from a systematically higher illiquidity? Positive externalities to nearby located rental markets may arise from local labor market condition in the urban agglomeration. A more efficient labor market in the center attracts a large share of qualified human capital and specialized labor force (see, e.g., Glaeser and Gottlieb (2009)). For instance, Eeckhout, Pinheiro, and Schmidheiny (2014) show how the productivity of highly skilled workers and of the less skilled service sector reinforces each other in urban centers. As a consequence, individual households prefer to live nearby these agglomeration centers (Chen and Rosenthal (2008)). Therefore, their location choice has an impact on local housing market liquidity.

This paper analyzes the impact of urban agglomerations on the liquidity of local rental housing markets. In an economic environment of low income growth, not keeping pace with rising house prices, and stricter bank lending requirements in many countries, particularly after the recent financial crisis period, and consequently high user costs of home ownership, the rental housing market becomes more important.[1] I empirically test the systematic exposure of local rental market liquidity to the proximity to urban centers. In the context of housing markets, liquidity is defined as the individual time on the market, i.e., the time until the offered property is sold or rented out (e.g., Han and Strange (2015)). Property transactions and rent agreements involve large search and matching costs for the buyer and seller as well as for the landlord and potential tenants, respectively. Because of these search frictions, the (rental) price and the individual liquidity of the heterogeneous housing units are jointly determined as the equilibrium outcome.

I focus on the rental housing market in Switzerland. The Swiss housing market provides an ideal testing ground to understand the cross-sectional variation of local rental

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

market liquidity. First, homeownership rates in Switzerland are among the lowest compared to international standards.[2] The high rate of realized tenancies provides an extensive dataset to learn about the liquidity in thinly traded rental housing markets. Second, the average age of homeowners in Switzerland shifted from 54 in 2000 to 57 in 2016. Among the 35-year old individuals, only 22% own a house. Switzerland also has a high immigration rate, with 94% of the immigrants renting apartments in the first years. [3] These highly skilled demographic groups prefer to live in attractive business locations. 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 the relation between local market liquidity and agglomeration externalities.

I exploit offers of listed rent adverts that are collected from Swiss online research platforms. The sample ranges from 2004 to 2015. I compute several proxies of local liquidity in segmented rental housing market. Each measure covers a different liquidity dimension of the market structure, such as the transaction volume, the market inventory, and the time on the market. I compare the liquidity proxies and discuss their economic implications for the market participants. Furthermore, I provide a systematic analysis of the cross-sectional variation among local market liquidity. In a first step, I provide empirical evidence of a decreasing liquidity gradient, i.e., an implied negative slope of the relation between the geographic distance from the local rental market to the urban agglomeration center and the corresponding local market liquidity.

In a second step, I analyze the exposure of local liquidity to urban agglomeration externalities. The identification strategy is based on the interaction of the cross-sectional variation in the geographic distance to the urban center with the economic performance

[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 provided by a report from Credit Suisse (2016).

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 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 the effect of positive agglomeration externalities on local market liquidity is attenuating with increasing distance between the rental market and the 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 analyze the economic implications of systematic liquidity from the perspective of investors, who buy rental units to rent them out. I show that more thinly traded, illiquid markets provide a lower income component that can be obtained from the rental cash flow stream. My findings suggest that this is related to the rental price discount that must be offered by the landlords as an incentive for potential tenants to rent in these less attractive 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 participants. For instance, a systematic lower local market liquidity confronts potential tenants with higher search costs and exposes landlords to a higher liquidity risk.

Compared to the previous literature, 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 the house (Head and Lloyd-Ellis (2012)). Therefore, he is exposed to liquidity. However, in the rental market, liquidity is less relevant for the potential tenant and his location choice. While the landlord is fully exposed to the time on the market, tenants care more about the supply of rental units, its availability, and its affordability.

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 that implies that households are indifferent between different 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 factors, has also important implications for the participants in the rental market and provides a guidance for targeted government interventions. The housing tenure choice of households depends on individual preferences, wealth considerations, and the living horizon in a specific location (see, e.g., Sinai and Souleles (2005)). Furthermore, agglomeration externalities influence the mobility decision of households over their life-cycle (Chen and Rosenthal (2008)). The location choice of potential tenants is particularly relevant for landlords. The rental cash flow stream 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. In this context, I discuss the role of the tenant as a potential liquidity supplier. I then derive several empirically testable hypotheses about the relation between local rental market liquidity and urban agglomeration externalities.

**Market Structure:** 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.[4] Housing markets are geographically segmented and households specialize their search focus within the preferred geographic location they want to live in (e.g., Piazessi, Schneider, and Stroebel (2014)).

Online real estate portals channel the asymmetric information between the participants about the housing heterogeneity in local rental markets to centralized platforms that facilitate a more efficient search and matching process. Online real estate platforms can be described as one-sided search markets (Williams (2014)). Property owners release the rent offers in the online market platform. Potential tenants can screen the listed entries and search for the optimal offer according to their individual preferences. The self-selection of potential tenants reduces the search costs of property owners who shift

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

the search incentives to their trading counterparty. As a consequence, the landlord is exposed to the opportunity cost of not realized rental income that is implied by the waiting time until a rental agreement is realized with a tenant. In this market platform, the landlord represents the demand-side of liquidity. The potential tenant acts as a liquidity provider in this one-sided search market, who is required for the rent offer to be removed from the online platform.

For illustration, I give two examples: Consider a tight, local market where the demand is larger than the supply for vacant, rental units. An example for such rental market might be the location of an urban agglomeration center. The competition among potential tenants for the scarce availability of rental offers increases the rent level, thereby lowering the affordability of potential tenants, and lowering the time on the market. From perspective of the landlord, such a market is highly liquid. In contrast, a local rental market in a more rural region might be characterized by a large supply of vacant rental space and a low potential demand. Landlords are confronted with a systematic illiquidity, represented by a high time on the market, that is reflected in high opportunity costs of sacrificed rental cash flows. Several papers, such as Krainer (2001), Genesove and Han (2012), Head, Lloyd-Ellis, and Sun (2014), find evidence of negatively correlated transaction prices and the time on the market in the owner-occupied housing market.

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

The first hypothesis derives from the standard urban rent gradient model. The location choice of individual households follows the compensation principle. Households who have higher commuting costs to travel to the urban center, as implied by a larger geographic distance, are compensated by lower rents. This spatial equilibrium condition must hold to ensure that households are indifferent between different locations. If this compensation principle is violated, individual households have an incentive to relocate.

The economic intuition about a potential liquidity gradient follows as a direct implication from the rent gradient. Market liquidity is jointly determined with the rental price as an equilibrium outcome of individual rent agreements between property owners and tenants. The joint determination of both variables predicts that liquidity also decreases with increasing distance from 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; following the joint determination of the equilibrium outcome, the liquidity gradient is accompanied by the rent gradient.*

Agglomeration externalities increase the attractiveness of urban centers because of a higher productivity and corresponding wage levels. The externality effect is accompanied with a better infrastructure and superior amenities, such as a more diverse cultural variety and better schooling. These pull factors have a positive direct impact on the market liquidity in the urban centers. The indirect spillover effect on nearby located rental markets decreases with increasing distance since households residing in these municipalities have to accept higher commuting costs to benefit from the agglomeration externalities. More distant rental markets are exposed to a systematic liquidity risk that can lead to potential liquidity dry-outs. Online market platforms improve the transparency of the rental markets and enable the potential tenant to learn about the trading activity in local markets. For instance, potential tenants can use the information given by the number of listed offers that are removed from the market and the time on the market of the individual properties to distinguish between attractive municipalities with excessive housing demand and systematically less attractive, thinly traded markets. While potential tenants focus the search incentives in attractive market segments, the illiquidity in thinly traded local markets intensifies by the lack of further liquidity supplied by the tenants.

**Hypothesis 2:** *The impact of agglomeration externalities in urban centers on local rental markets attenuates with increasing geographic distance between both locations; they* *have a positive effect on the liquidity in the urban center, while more distant rental markets are exposed to a systematic liquidity risk and potential liquidity dry-outs.*

Systematic illiquidity leads to a higher expected time on the market of the listed rental offers and exposes the landlord to the opportunity cost of not realized rental cash flow streams. 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 stream that can be obtained from investments in the rental market. More specifically, the capitalization rate, defined as the current income that can be obtained per currency unit of the 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 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] Table 1 provides a descriptive summary of the rental price offers and

[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.

the corresponding hedonic attributes for the cross-sectional listings. The average offered rent equals CHF 1665.97. The tenancy law in Switzerland allows rental price adjustments for established rent agreements only within a range around the fluctuations of a reference mortgage rate. However, landlords can freely set their offered rental prices. I use the listed rent offer as proxy for the realized rental price. Concerns about a potential bias in the rental price when the offered value is used as a proxy, can be mitigated by the following argumentation: First, Genesove and Mayer (2001) interpret the offered property 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. 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]

Based on the release and the removal 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 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]

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

Figure 2 shows the cross-sectional distribution of the listed rent offers from 2004 to 2015. For each municipality, the number of observed listings 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 market activity 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 compute the local liquidity measure 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

[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.

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 liquidity proxy by the local rental housing stock $S_{it}$ in the municipality $i$ at time period $t$ to account for the heterogeneity in the rental market size. The normalization makes the liquidity measures comparable across local markets with different supply-side restrictions. 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 a a rough proxy for the local liquidity in rental markets. 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 provides an indication of a thinly traded, local market, that suffers from the lack of liquidity supplied by potential 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 inventory risk for the landlord in terms of high vacancy rates, a long time on the market, and higher implied opportunity costs of lost income from rental cash flows. The turnover rate also provides an intuition about the market activity of the liquidity suppliers, i.e., the potential tenants. For instance, 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.

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, the average 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.

***Duration-Based Measures:*** I compute the expected time on the market for each municipality. A higher duration is associated with an increase in the implicit opportunity cost of lost rental income for the property owner. 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) price-impact measure, I compute a version that accounts for the specific characteristics of rental markets.[9] Rental prices are sticky over time. The limited fluctuation of rents to adjust in equilibrium must be compensated by the variation in the property-specific liquidity. Therefore, I measure the systematic impact of the realized transaction volume on the expected time on the market,

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

This measure serves as a proxy for the local market illiquidity that captures the extent to which the realized transaction volume has a systematic impact on the expected time on the market. For instance, as rental prices are too sticky to adjust to an increasing local trading activity, the effect is channeled to the average duration that must decrease. Similarly, 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 indicates a systematic less liquid rental market.

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 liquidity proxies (trading volume, inventory share, and turnover rate) are positively related to each other and show a negative association with the illiquidity measures (average time on the market and the duration impact).

[INSERT TABLE 2 HERE]

In the next step, I follow Pastor and Stambaugh (2003) and compute the the market-wide liquidity as the cross-sectional average of the individual local market levels. I rank the average level based on the quartiles of the geographic distance distribution from the

[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 measures 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.

agglomeration center to 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 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 local agglomeration centers, I use the Credit Suisse Site Quality Index. This index is annually released since its launch in 1997, with a fully methodological update provided in 2004, the starting period of the dataset. The index ranks 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, for instance, the connectivity to a local airport.

To isolate the systematic effect of agglomeration externalities from nearby located urban centers on the cross-sectional variation in 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 con-

[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.

founding 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. The following covariates are selected from the Swiss Bureau of Statistics:

*Vacancy Rate:* I control for the annual vacancy rate in the local market that serves as a proxy for the annual excess supply of rental offers by the local landlords. The vacancy rate can differ across local markets. This heterogeneity depends on differences in local demand and supply as well as trading frictions. These market-specific frictions can cause a systematic mismatch between landlords and tenants (Wheaton (1990)).

*Supply Inelasticity:* Saiz (2010) proposes regional geographic land constraints as a proxy for the inelastic housing supply. Similarly, Glaeser, Gyourko, and Saks (2005) argue that the house price variation can be explained by policy-induced zoning restrictions and land use regulations. Therefore, I use the percentage share of undevelopable land per municipality to account for the potential land scarcity and housing supply inelasticity. From a technical point of view, the supply inelasticity can also be removed by municipality fixed effects. However, I include the share of undevelopable land as a control variable for two reasons: First, the 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 allows to estimate the sensitivity of local liquidity to supply inelasticity.

*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 provided for 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 also consider the demographic trend in the municipality. The population growth reflects the local demand-side of the housing market. A higher local population is positively related to the demand for goods that are produced by the industrial and service sector. To account for differences in economic growth and corresponding income levels, I exploit the cross-sectional variation in the inflow of qualified workforce that is related to the local labor market condition. For this, I use the annual rate of cross-border commuters residing in neighboring municipalities.

Table 3 presents a descriptive summary of the selected covariates.

[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. 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 $\varepsilon_{it}$ and the distance measure $Distance_i$ (see, e.g., Imbens (2004)). Conditional on adjusting for all observed 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.[11]

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 assumption in more detail. A potential violation of the assumption would contaminate

[11] 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, $E[Liquidity_{it}(d)|Distance, X_{it}] = E[Liquidity_{it}(d)|X_{it}]$.

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 are simultaneously related to the local liquidity and the geographic position of the market 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 instead of in large cities. These households reside in the close proximity to natural landscapes, such as forests, mountains, and lakes. Therefore, I control for systematic differences between urban and rural local markets. These covariates capture the degree to urbanization and account for the cultural background in terms of the spoken language. For instance, the location choice might be influenced by the desire of individuals to live in a neighborhood with a high cultural familiarity. Furthermore, the cross-sectional variation in the market liquidity can be explained by systematic differences across the cantons to which local markets are classified.[12] For instance, the canton-level performance provides an incentive for households to move to municipalities within the canton. Therefore, I additionally control for the canton-level based unemployment rate, the GDP, and the taxation of the median gross income of CHF 50.000, conditional on the marital status and the total number of children. I also exploit canton-fixed effects to mitigate the potential endogeneity arising from time-invariant unobservable components.

While 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

[12]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.

unrelated to the explanatory variable of interest of 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, the individual location choice is not affected by the geographic distance.[13]

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 ignore potential spatial interaction effects that might affect the relocation of households within the local neighborhood. 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 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 nonparametric 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

[13]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).

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 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 illiquidiy discount in local 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)) proxy illiquidity and 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. For instance, conditional on the covariates, an additional kilometer in distance from the agglomeration center decreases the transaction volume in the local market by 3.1%.[14] The inference is based on clustered standard errors to account for potential spatial dependence across local markets.

Regarding the control variables, the signs of the estimated coefficients are in line with the economic intuition. A higher vacancy rate is positively related to the market liquidity. A larger supply of vacant space in the rental market results in lower search costs of households to find rental units. In terms of liquidity, the higher liquidity demand of landlords, as captured by the vacancy rate, facilitates a faster matching with the liquidity supply of potential tenants. The local market conditions, i.e., population growth and the percentage of undevelopable land are also positively related to liquidity. Population growth captures the demand-side and is a proxy for an increase in the liquidity supplied by 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

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

distance to the urban agglomeration center. The estimated coefficient of the liquidity 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 the 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 3.9% based on the Hirano and Imbens (2004) approach, 2.5% based on the weighted least square approach with the parametric specification of the propensity score, and 3.3% based on the estimates using the non-parametric specification of the propensity score.

[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:

$$Liquidity_{it} = \beta_0 + distance_i \beta_1 + SQI_t \beta_2 + distance_i \times SQI_t \beta_3 + X_{it}^{\prime} \delta + \varepsilon_{it} \tag{8}$$

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 44.1% 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 1.6%-points with each additional unit in distance from the center. Similar effects can be observed for the other liquidity measures, except of the market-specific average time on the market.[15]

[INSERT TABLE 6 HERE]

To elaborate the effect of agglomeration externalities on the systematic liquidity risk, 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 performance of the urban center over time. 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 serve as a pull factor and 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 liquidity risk for the landlord.[16]

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

[15]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 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.

[16]Table D.6 in the Online 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.

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 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 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 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 for 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.[17]

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 that add 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

[17]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.

Hansen (2014a)). Table 8 presents the regression results based on different pre-selection methods.[18] The estimated coefficients are similar to those from the the baseline OLS regression without pre-selection. 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. This is in line with the economic intuition. Landlords offer a rental price discount on the offered rental unit to attract 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 can obtain as a landlord 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. 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 and should help to improve the understanding of the participants about the rental market.

The paper also contributes to the understanding of the systematic effect of urban agglomeration centers on the local market liquidity. I first provide empirical evidence of

[18] 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.

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 pull factors of the agglomeration center absorbs the liquidity from less attractive local housing market. I also find empirical evidence that the compensation required by the potential tenant to provide liquidity in thinly traded, illiquid rental markets leads to systematically lower capitalization rates that can be earned by property investors. Hence, the cross-sectional variation in the performance of property investors can be related to market liquidity.

The results have important implications for the market participants and provide relevant insights for policy implications. For instance, tenants are exposed to the systematic liquidity risk 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. From a policy perspective, the empirical results suggest that, in order to improve the liquidity in less attractive 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 the rental housing markets.

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Table 1: Hedonic Characteristics

This table shows the descriptive summary of the hedonic characteristics. All variables are based on all information that is listed in the individual rental housing offers from 2004 to 2015. 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.** |
|---|---|---|---|---|---|
| Rent Offer | 1665.97 | 924.51 | 201 | 15000 | 2183944 |
| Duration | 53.24 | 77.36 | 1 | 1000 | 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-values. 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 of Control Variables

This Table 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. The commuting area is defined as the local labor market surrounding the center, following the definition of the Swiss Statistical Office. Growth rates are determined as percentage changes. The sample ranges from 2004 to 2015.

| | **Mean** | **Std.Dev.** | **Min** | **Max** | **Obs.** |
|---|---|---|---|---|---|
| Site Quality Index (SQI) | 1.13 | 0.87 | -0.30 | 3.30 | 11283 |
| Vacancy Rate | 0.05 | 0.08 | 0.00 | 0.94 | 12277 |
| Undevelopable Land | 0.20 | 0.17 | 0.02 | 0.98 | 12705 |
| $\Delta$ Infrastructure | 0.07 | 1.23 | -9.42 | 11.60 | 12318 |
| $\Delta$ Population | 0.01 | 0.03 | -0.28 | 0.33 | 12339 |
| $\Delta$ Commuter | 0.04 | 0.37 | -3.01 | 3.82 | 12234 |

Table 4: Liquidity Gradient

This Table shows the regression results of the liquidity gradient for the different local liquidity measures: trading volume (Model 1), the inventory share (Model 2), the turnover rate (Model 3), the average time on the market (Model 4), and the duration impact of trading volume (Model 5). The geographic distance is computed as the Haversine distance measured in kilometers to capture the shape of the earth. The covariates include 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.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Distance | -0.031*** | -0.031*** | -0.028*** | 0.006* | 0.044*** |
| | (0.004) | (0.005) | (0.004) | (0.004) | (0.008) |
| Vacancy Rate | 3.473*** | 2.917*** | 3.017*** | 0.675** | -2.228*** |
| | (0.277) | (0.453) | (0.441) | (0.329) | (0.754) |
| Δ Population | 6.810*** | 2.433*** | 2.424*** | 2.985*** | 0.776 |
| | (0.766) | (0.922) | (0.891) | (0.721) | (1.478) |
| Undevelopable Land | 1.824*** | 5.442*** | 5.330*** | -3.700*** | -9.123*** |
| | (0.265) | (0.338) | (0.341) | (0.287) | (0.589) |
| Δ Commuter | 0.113*** | 0.227*** | 0.225*** | -0.110*** | -0.346*** |
| | (0.026) | (0.048) | (0.040) | (0.032) | (0.067) |
| Δ Infrastructure | 0.056*** | 0.027* | 0.019 | 0.032*** | -0.010 |
| | (0.010) | (0.014) | (0.012) | (0.008) | (0.021) |
| Observations | 10273 | 10335 | 10335 | 9853 | 10273 |
| Year dummies | Yes | Yes | Yes | Yes | Yes |
| Adj.-$R^2$ | 0.282 | 0.371 | 0.409 | 0.297 | 0.385 |

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 (Model 1), the inventory share (Model 2), the turnover rate (Model 3), the average time on the market (Model 4), and the duration impact of trading volume (Model 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 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.

| | **(1)** | | | **(2)** | | | **(3)** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **HI** | **pCBPS** | **npCBPS** | **HI** | **pCBPS** | **npCBPS** | **HI** | **pCBPS** | **npCBPS** |
| Distance | -0.039*** | -0.025*** | -0.033*** | -0.020*** | -0.012*** | -0.017*** | -0.058*** | -0.020*** | -0.035*** |
| | (0.001) | (0.002) | (0.003) | (0.001) | (0.001) | (0.001) | (0.076) | (0.002) | (0.003) |
| Vancancy Rate | | 3.288*** | 3.428*** | | 3.365*** | 3.445*** | | 2.693*** | 2.660*** |
| | | (0.151) | (0.155) | | (0.134) | (0.129) | | (0.240) | (0.275) |
| Δ Population | | 6.868*** | 6.772*** | | 5.478*** | 5.425*** | | 2.559*** | 1.016 |
| | | (0.513) | (0.510) | | (0.431) | (0.427) | | (0.642) | (0.998) |
| Undevelopable Land | | 2.645*** | 2.310*** | | 1.407*** | 1.093*** | | 6.269*** | 5.912*** |
| | | (0.082) | (0.095) | | (0.080) | (0.083) | | (0.102) | (0.113) |
| Δ Commuter | | 0.129*** | 0.146*** | | 0.080*** | 0.088** | | 0.182*** | 0.211*** |
| | | (0.028) | (0.027) | | (0.023) | (0.022) | | (0.042) | (0.047) |
| Δ Infrastructure | | 0.058*** | 0.039*** | | 0.041*** | 0.046*** | | 0.024 | -0.040 |
| | | (0.013) | (0.024) | | (0.041) | (0.012) | | (0.016) | (0.030) |
| Propensity Score | -4.470*** | | | -1.317 | | | -25.172*** | | |
| | (1.337) | | | (1.212) | | | (1.889) | | |
| Observations | 10270 | 10266 | 10266 | 10332 | 10266 | 10328 | 10332 | 10328 | 10328 |
| Adj.-$R^2$ | 0.123 | | | 0.048 | | | 0.126 | | |
| AIC | | 31254 | 31346 | | 31254 | 28487 | | 36113 | 36683 |

*Table 5 continued.*

| | | (4) | | | (5) | |
|---|---|---|---|---|---|---|
| | **HI** | **p CBPS** | **np CBPS** | **(HI)** | **p CBPS** | **np CBPS** |
| Distance | 0.028*** | 0.005*** | 0.003 | 0.094*** | 0.031*** | 0.040*** |
| | (0.001) | (0.001) | (0.002) | (0.003) | (0.003) | (0.005) |
| Vancancy Rate | | 0.802*** | 0.591*** | | -1.608*** | -1.496*** |
| | | (0.121) | (0.187) | | (0.370) | (0.387) |
| Δ Population | | 2.580*** | 1.290* | | -1.914* | -1.283 |
| | | (0.436) | (0.760) | | (1.124) | (1.157) |
| Undevelopable Land | | -3.801*** | -3.731*** | | -10.331*** | -9.589*** |
| | | (0.069) | (0.089) | | (0.179) | (0.192) |
| Δ Commuter | | -0.119*** | -0.173*** | | -0.372*** | -0.440*** |
| | | (0.027) | (0.036) | | (0.075) | (0.072) |
| Δ Infrastructure | | 0.029*** | -0.009 | | -0.023 | -0.0003 |
| | | (0.011) | (0.023) | | (0.028) | (0.036) |
| Propensity Score | 18.610*** | | | 40.665*** | | |
| | (1.516) | | | (3.330) | | |
| Observations | 9850 | 9846 | 9846 | 10270 | 10266 | 10266 |
| Adj.-$R^2$ | 0.062 | | | 0.116 | | |
| AIC | | 28753 | 29185 | | 47096 | 47246 |

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 (Model 1), the inventory share (Model 2), the turnover rate (Model 3), the average time on the market (Model 4), and the duration impact of trading volume (Model 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 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.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Distance | -0.019*** | -0.024*** | -0.019** | 0.005 | 0.024* |
| | (0.007) | (0.009) | (0.008) | (0.006) | (0.013) |
| SQI | 0.441*** | 0.319* | 0.375** | 0.015 | -0.528* |
| | (0.113) | (0.172) | (0.159) | (0.130) | (0.272) |
| SQI $\times Distance$ | -0.016*** | -0.013** | -0.014** | 0.001 | 0.023** |
| | (0.005) | (0.007) | (0.006) | (0.004) | (0.010) |
| Vacancy Rate | 2.937*** | 1.860*** | 1.914*** | 1.271*** | -0.390 |
| | (0.302) | (0.443) | (0.415) | (0.334) | (0.691) |
| Δ Population | 3.614*** | 1.974** | 1.629** | 0.652 | -2.334* |
| | (0.626) | (0.877) | (0.786) | (0.620) | (1.365) |
| Undevelopable Land | 1.696*** | 5.225*** | 5.250*** | -3.593*** | -8.876*** |
| | (0.221) | (0.333) | (0.326) | (0.294) | (0.585) |
| Δ Commuter | 0.051** | 0.153*** | 0.137*** | -0.130*** | -0.327*** |
| | (0.024) | (0.043) | (0.035) | (0.028) | (0.061) |
| Δ Infrastructure | 0.031*** | 0.027* | 0.017 | 0.017** | -0.018 |
| | (0.010) | (0.014) | (0.012) | (0.009) | (0.021) |
| Observations | 9290 | 9351 | 9351 | 8888 | 9290 |
| Canton Fixed-Effects | Yes | Yes | Yes | Yes | Yes |
| Adj.-$R^2$ | 0.460 | 0.457 | 0.520 | 0.409 | 0.477 |

Table 7: Effect on Liquidity Risk

This table shows regression results of the performance of urban agglomeration centers on the liquidity risk in local markets over time. The different liquidity measures are the trading volume (Model 1), the inventory share (Model 2), the turnover rate (Model 3), the average time on the market (Model 4), and the duration impact of trading volume (Model 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 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.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| SQI | -0.275*** | -0.224*** | -0.234*** | 0.035** | 0.337*** |
| | (0.035) | (0.047) | (0.028) | (0.014) | (0.054) |
| Vacancy Rate | 0.650*** | 0.474** | 0.389*** | 0.258*** | 0.006 |
| | (0.175) | (0.234) | (0.145) | (0.072) | (0.223) |
| Δ Unemployment | -0.398*** | -0.119** | -0.109*** | 0.199*** | 0.774*** |
| | (0.039) | (0.056) | (0.034) | (0.014) | (0.065) |
| Δ Population | 0.314 | 0.673 | 0.188 | -0.187 | -0.847 |
| | (0.432) | (0.555) | (0.386) | (0.133) | (0.582) |
| Δ Infrastructure | 0.020** | 0.022* | 0.014* | 0.004 | -0.015 |
| | (0.008) | (0.012) | (0.008) | (0.003) | (0.012) |
| Interest Rate | -0.092*** | -0.034*** | -0.034*** | 0.031*** | 0.152*** |
| | (0.007) | (0.010) | (0.006) | (0.002) | (0.010) |
| Δ Commuter | -0.031* | -0.002 | -0.018 | -0.010 | 0.012 |
| | (0.018) | (0.030) | (0.016) | (0.007) | (0.030) |
| Δ Migration | 2.162** | -12.228*** | -11.300*** | -12.021*** | -24.892*** |
| | (0.982) | (1.259) | (0.899) | (0.359) | (1.261) |
| Observations | 9240 | 9302 | 9302 | 8838 | 9240 |
| Fixed-Effects | Yes | Yes | Yes | Yes | Yes |
| Adj.-$R^2$ | 0.063 | 0.031 | 0.067 | 0.266 | 0.116 |

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 (Model 1), the inventory share (Model 2), the turnover rate (Model 3), the average time on the market (Model 4), and the duration impact of trading volume (Model 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.

| Effect of Market Liquidity | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| 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 |

Figure 1: Survival Analysis of Time on the Market

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.

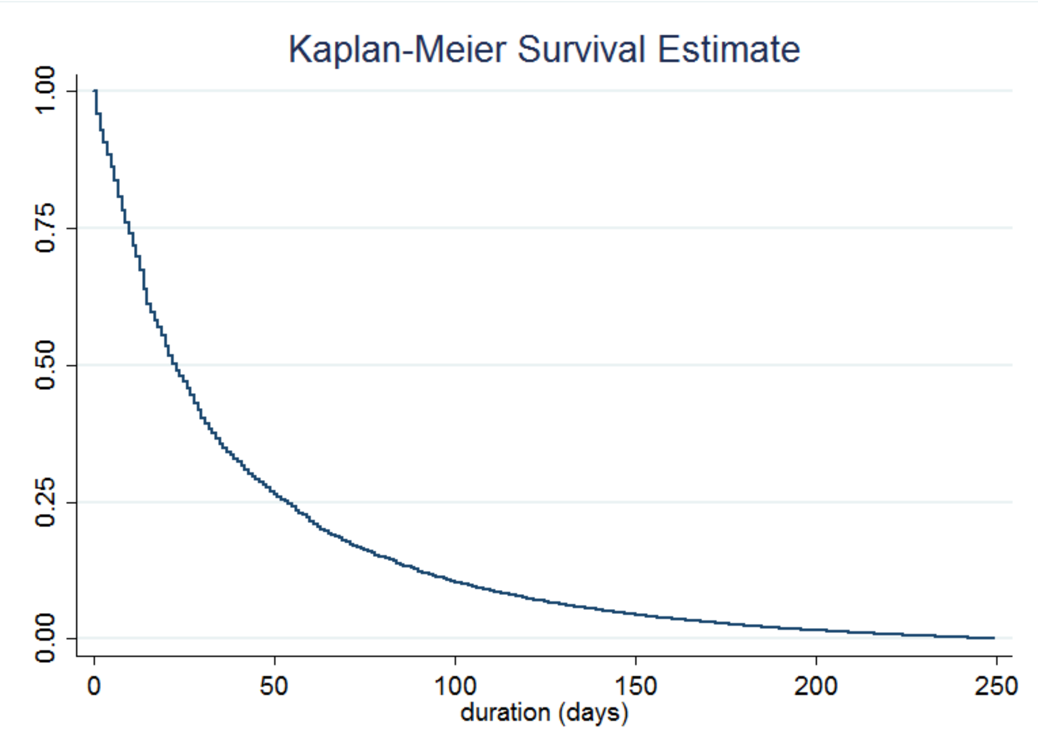

Figure 2: Cross-Sectional Distribution of Listed Rental Offers

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.

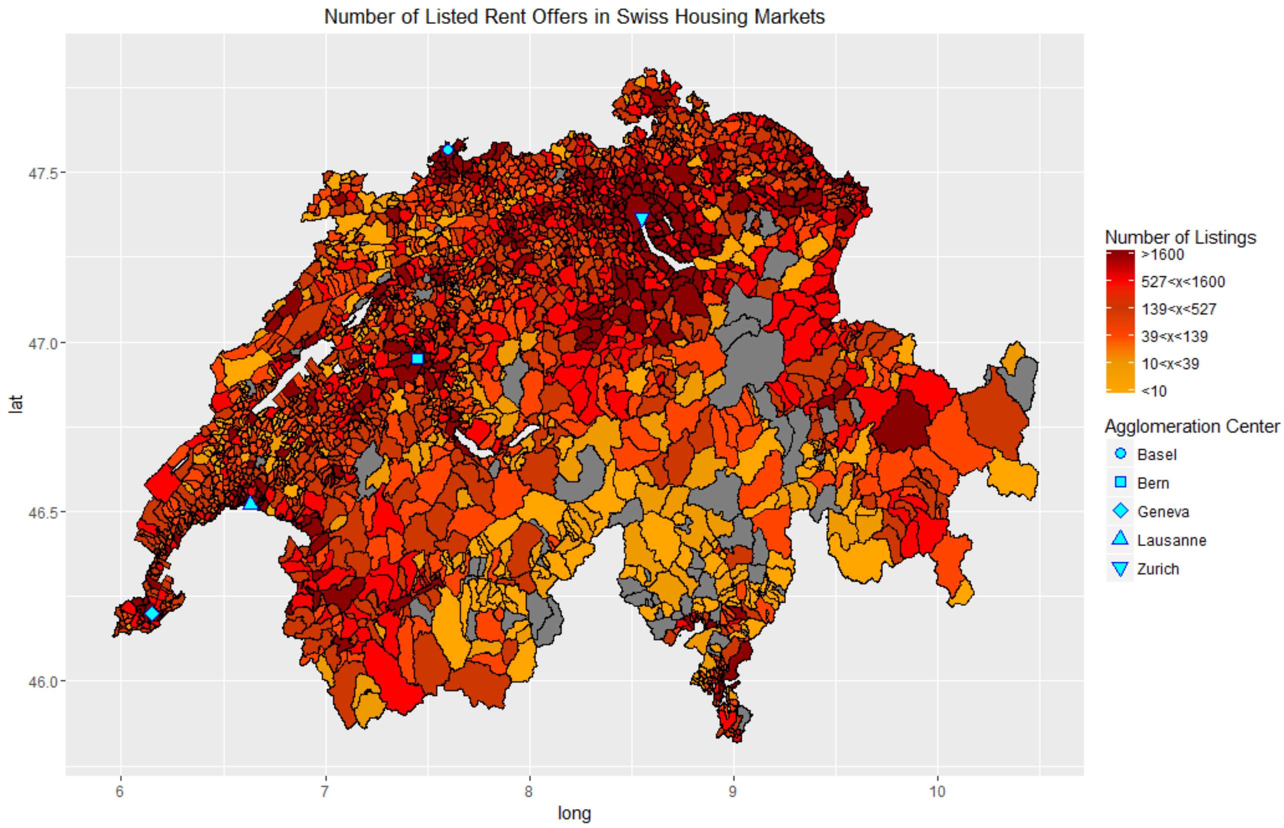

Figure 3: Market-wide Liquidity in Rental Housing Markets

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 *

November 16, 2016

**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

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

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

**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

[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

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

and the balancing weights are given by

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

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 covariance matrix $\Sigma_\theta(T_i, X_i)$.

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

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

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

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

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 $\rho$ 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 $\rho$ 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 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 $\gamma_1$ and $\gamma_2$ 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 $\beta$ 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 $\gamma_{lasso,1} = argminE(Y_i - \sum_{p=1}^{P} x_{i,p}\gamma_{p,1})^2 + \lambda \sum_{p=1}^{P} \mid b_p \mid \omega_{jp}$ and $\gamma_{lasso,2} = argminE(T_i - \sum_{p=1}^{P} x_{i,p}\gamma_{p,1})^2 + \lambda \sum_{p=1}^{P} \mid b_p \mid \omega_{jp}$, respectively. The tuning parameter $\lambda$ and the penalty loadings $\omega_j$ 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 |

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 (Model 1), the inventory share (Model 2), the turnover rate (Model 3), the average time on the market (Model 4), and the duration impact of trading volume (Model 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 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.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Distance | -0.027* | -0.038*** | -0.026* | 0.010 | 0.042* |
| | (0.015) | (0.004) | (0.014) | (0.011) | (0.022) |
| Distance$^2$ | -0.000 | 0.000* | -0.000 | -0.006 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Vacancy Rate | 3.462*** | 2.950*** | 3.013*** | 0.660** | -2.228*** |
| | (0.279) | (0.177) | (0.438) | (0.324) | (0.746) |
| Δ Population | 6.802*** | 2.458*** | 2.418*** | 2.976*** | -0.767 |
| | (0.774) | (0.622) | (0.891) | (0.719) | (1.475) |
| Undevelopable Land | 1.859*** | 5.356*** | 5.341*** | -3.658*** | -9.124*** |
| | (0.296) | (0.100) | (0.356) | (0.295) | (0.606) |
| Δ Commuter | 0.113*** | 0.227*** | 0.225*** | -0.110*** | -0.346*** |
| | (0.026) | (0.040) | (0.040) | (0.032) | (0.067) |
| Δ Infrastructure | 0.056*** | 0.027* | 0.019 | 0.032*** | -0.010 |
| | (0.010) | (0.015) | (0.012) | (0.008) | (0.020) |
| Observations | 10273 | 10335 | 10335 | 9853 | 10273 |
| Year dummies | Yes | Yes | Yes | Yes | Yes |
| Adj.-$R^2$ | 0.281 | 0.372 | 0.410 | 0.297 | 0.386 |

## 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 (Model 1), the inventory share (Model 2), the turnover rate (Model 3), the average time on the market (Model 4), and the duration impact of trading volume (Model 5). 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.

| | (1) | | | | (2) | | | |
|---|---|---|---|---|---|---|---|---|
| | (a) | (b) | (c) | (d) | (a) | (b) | (c) | (d) |
| Distance | -0.032*** | -0.027*** | -0.017*** | -0.013*** | -0.035*** | -0.030*** | -0.033*** | -0.016*** |
| | (0.001) | (0.004) | (0.004) | (0.004) | (0.006) | (0.005) | (0.006) | (0.005) |
| Vancancy Rate | 2.971*** | 2.922*** | 3.275*** | 3.030*** | 1.727*** | 2.058*** | 2.068*** | 2.644*** |
| | (0.114) | (0.256) | (0.274) | (0.262) | (0.394) | (0.423) | (0.422) | (0.402) |
| Δ Population | 3.587*** | 6.035*** | 5.935*** | 6.168*** | 2.689*** | 2.769*** | 4.658*** | 1.615* |
| | (0.394) | (0.703) | (0.683) | (0.708) | (0.814) | (0.883) | (0.897) | (0.861) |
| Undevelopable Land | 1.699*** | 1.544*** | 1.871*** | 0.888*** | 5.239*** | 5.263*** | 5.360*** | 3.944*** |
| | (0.059) | (0.246) | (0.265) | (0.252) | (0.317) | (0.325) | (0.330) | (0.308) |
| Δ Commuter | 0.039 | 0.089*** | 0.112*** | 0.086*** | 0.161*** | 0.218*** | 0.208*** | 0.140*** |
| | (0.025) | (0.025) | (0.026) | (0.023) | (0.040) | (0.046) | (0.043) | (0.041) |
| Δ Infrastructure | 0.034*** | 0.054*** | 0.048*** | 0.055*** | 0.032** | 0.032** | 0.046*** | 0.027** |
| | (0.009) | (0.010) | (0.010) | (0.010) | (0.013) | (0.014) | (0.014) | (0.013) |
| Δ Unemployment | | -0.079** | | | | -0.062 | | |
| | | (0.040) | | | | (0.057) | | |
| $\text{Tax}_{married,0child.}$ | | -0.0003*** | | | | -0.0003*** | | |
| | | (0.000) | | | | (0.000) | | |
| $\text{Tax}_{married,2child.}$ | | 0.001*** | | | | 0.001*** | | |
| | | (0.000) | | | | (0.000) | | |
| $\text{Tax}_{single,2child.}$ | | -0.001*** | | | | -0.0001 | | |
| | | (0.000) | | | | (0.000) | | |
| $\text{Language}_{french}$ | | | -0.075 | | | | -0.729*** | |
| | | | (0.064) | | | | (0.096) | |
| Observations | 10273 | 10273 | 10273 | 10273 | 10335 | 10335 | 10335 | 10335 |
| 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.-$R^2$ | 0.460 | 0.343 | 0.321 | 0.361 | 0.460 | 0.400 | 0.400 | 0.437 |

*Table D.3 continued.*

| | (3) | | | | (4) | | | | (5) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **(a)** | **(b)** | **(c)** | **(d)** | **(a)** | **(b)** | **(c)** | **(d)** | **(a)** | **(b)** | **(c)** | **(d)** |
| Distance | -0.031*** | -0.027*** | -0.028*** | -0.012*** | 0.007* | 0.006* | 0.018*** | 0.005 | 0.044*** | 0.041*** | 0.051*** | 0.020*** |
| | (0.005) | (0.005) | (0.005) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.009) | (0.008) | (0.009) | (0.007) |
| Vancancy Rate | 1.771*** | 2.105*** | 2.178*** | 2.710*** | 1.302*** | 1.052*** | 1.329*** | 0.701** | -0.381 | -0.879 | -0.638 | -1.644*** |
| | (0.378) | (0.404) | (0.411) | (0.384) | (0.308) | (0.316) | (0.304) | (0.301) | (0.655) | (0.700) | (0.686) | (0.633) |
| Δ Population | 2.374*** | 2.658*** | 4.617*** | 1.588* | 0.498 | 2.520*** | 0.073 | 2.887*** | 2.545** | -0.785 | -5.936*** | -0.196 |
| | (0.735) | (0.848) | (0.847) | (0.815) | (0.575) | (0.698) | (0.618) | (0.683) | (1.229) | (1.451) | (1.411) | (1.387) |
| Undevelopable Land | 5.257*** | 5.176*** | 5.320*** | 3.796*** | -3.645*** | -3.687*** | -3.564*** | -2.944*** | -8.964*** | -8.822*** | -8.969*** | -6.532*** |
| | (0.312) | (0.324) | (0.331) | (0.310) | (0.279) | (0.285) | (0.288) | (0.259) | (0.559) | (0.573) | (0.575) | (0.524) |
| Δ Commuter | 0.156*** | 0.216*** | 0.210*** | 0.140*** | -0.093*** | -0.146*** | -0.151*** | -0.109*** | -0.242*** | -0.397*** | -0.438*** | -0.318*** |
| | (0.032) | (0.038) | (0.035) | (0.033) | (0.025) | (0.032) | (0.028) | (0.027) | (0.054) | (0.067) | (0.061) | (0.058) |
| Δ Infrastructure | 0.020* | 0.023** | 0.037*** | 0.019* | 0.016** | 0.032*** | 0.016** | 0.032*** | -0.025 | -0.008 | -0.043** | -0.007 |
| | (0.011) | (0.038) | (0.012) | (0.011) | (0.008) | (0.008) | (0.007) | (0.008) | (0.019) | (0.020) | (0.020) | (0.020) |
| Δ Unemployment | | -0.019 | | | | 0.140*** | | | | 0.318*** | | |
| | | (0.043) | | | | (0.026) | | | | (0.074) | | |
| $\text{Tax}_{married,0child.}$ | | -0.0003*** | | | | -0.000 | | | | 0.0004** | | |
| | | (0.000) | | | | (0.000) | | | | (0.000) | | |
| $\text{Tax}_{married,2child.}$ | | 0.001*** | | | | -0.0003*** | | | | -0.001*** | | |
| | | (0.0001) | | | | (0.000) | | | | (0.000) | | |
| $\text{Tax}_{single,2child.}$ | | -0.0002** | | | | 0.0001*** | | | | 0.001*** | | |
| | | (0.000) | | | | (0.000) | | | | (0.000) | | |
| $\text{Language}_{french}$ | | | -0.726*** | | | | 0.570*** | | | | 1.250*** | |
| | | | (0.094) | | | | (0.078) | | | | (0.162) | |
| Observations | 10335 | 10335 | 10335 | 10335 | 9853 | 9853 | 9853 | 9853 | 10273 | 10273 | 10273 | 10273 |
| 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.-$R^2$ | 0.520 | 0.443 | 0.321 | 0.491 | 0.422 | 0.296 | 0.402 | 0.362 | 0.394 | 0.394 | 0.419 | 0.459 |

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 (Model 1), the inventory share (Model 2), the turnover rate (Model 3), the average time on the market (Model 4), and the duration impact of trading volume (Model 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.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Distance | -0.050*** | -0.073*** | -0.063** | 0.017 | 0.088*** |
| | (0.010) | (0.018) | (0.016) | (0.013) | (0.028) |
| Burglary | -0.142*** | -0.144** | -0.151*** | 0.015 | 0.230** |
| | (0.041) | (0.058) | (0.051) | (0.041) | (0.089) |
| Burglary $\times Distance$ | 0.004** | 0.006*** | 0.005** | -0.001 | -0.007* |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.004) |
| Vacancy Rate | 2.917*** | 1.003 | 1.004 | 1.919*** | 1.078 |
| | (0.3462) | (0.764) | (0.666) | (0.548) | (1.192) |
| $\Delta$ Population | 4.298*** | 4.889*** | 5.010*** | -1.122 | -6.536** |
| | (1.394) | (1.845) | (1.645) | (1.347) | (2.841) |
| Undevelopable Land | 1.609*** | 5.447*** | 5.384*** | -4.009*** | -9.600*** |
| | (0.372) | (0.524) | (0.504) | (0.460) | (0.908) |
| $\Delta$ Commuter | 0.058 | 0.130 | 0.157** | -0.073 | -0.249** |
| | (0.059) | (0.086) | (0.071) | (0.049) | (0.117) |
| $\Delta$ Infrastructure | 0.054** | 0.059 | 0.047 | 0.012 | -0.057 |
| | (0.023) | (0.037) | (0.033) | (0.022) | (0.053) |
| Observations | 3876 | 3889 | 3889 | 3800 | 3876 |
| Canton Fixed-Effects | Yes | Yes | Yes | Yes | Yes |
| Adj.-$R^2$ | 0.445 | 0.463 | 0.513 | 0.448 | 0.495 |

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 (Model 1), the inventory share (Model 2), the turnover rate (Model 3), the average time on the market (Model 4), and the duration impact of trading volume (Model 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.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $\text{Liquidity}_{center,t-1}$ | -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 (Model 1), the inventory share (Model 2), the turnover rate (Model 3), the average time on the market (Model 4), and the duration impact of trading volume (Model 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.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| 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) |
| $\Delta$ Unemployment | 0.095*** | 0.092*** | 0.084*** | 0.082*** | 0.070*** |
| | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| $\Delta$ Population | -1.092*** | -0.786*** | -0.754*** | -0.743*** | -0.702*** |
| | (0.103) | (0.101) | (0.101) | (0.102) | (0.101) |
| $\Delta$ Infrastructure | -0.012*** | -0.008*** | -0.008** | -0.011*** | -0.005 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| $\Delta$ 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) |
| $\Delta$ GDP | 0.386*** | 0.402*** | 0.329** | 0.347*** | 0.272** |
| | (0.130) | (0.128) | (0.129) | (0.130) | (0.128) |
| $\Delta$ 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) |
| $\Delta$ 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.

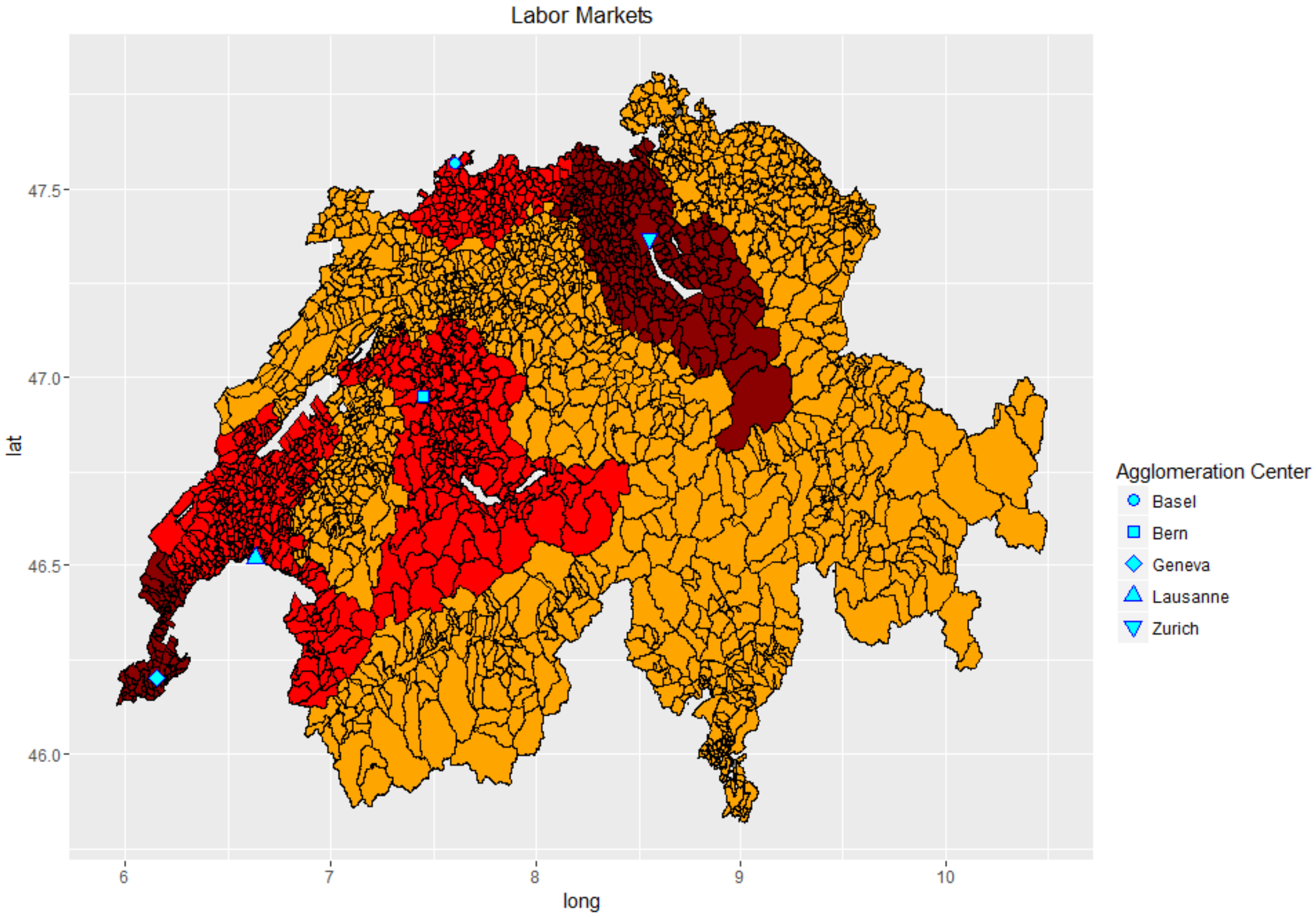

Figure C.2: Cross-Sectional Distribution of Local Liquidity

This figure provides the Box-Whiskers plots for each of the local liquidity measures: the trading volume, the counts of trading days, 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.