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AVERAGE TIME TO SELL A PROPERTY AND CREDIT CONDITIONS:
EVIDENCE FROM THE ITALIAN HOUSING MARKET SURVEY

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Average time to sell a property and credit conditions: evidence from Bank of Italy Housing Market Survey

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This study examines the effect of housing credit conditions on the Time on Market for residential properties in Italy, using a unique dataset from the Bank of Italy survey on the Italian housing market.

The analysis was carried out on a sample of roughly 1,000 real estate agents over the period 2011-2015 using panel data techniques. The results support the view that an increase in housing market liquidity, measured by the Loan-to-Value Ratio, reduces the average TOM of a property, thus improving the matching process between buyers and sellers. The results are found to be robust to specifications including the traditional determinants of TOM, used as controls (i.e. price revisions, potential buyers, mandates to sell, the role of brokers and so on). The results also show that a higher price reduction, possibly associated with an initial mispricing by the seller when setting the initial listing price, seems to be associated with a higher TOM for residential properties.

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1 Introduction

Due to matching frictions between buyers and sellers, residential properties are generally considered illiquid assets. Indeed, the matching process among buyers and sellers for a residential property in Italy can range from a few months to several years depending on the degree or 'thickness' of market development, households' financial constraints, house characteristics as well as the costs and taxation associated with such transactions. The selling time for a property, or Time on Market (TOM), is thus considered a key indicator of the housing market's state of health. It provides information on the marketability of a property as well as the degree of (il-) liquidity of the underlying real estate assets (Lippman and McCall, 1986 and Krainer, 2001).

The aim of this paper is to empirically investigate the effect of housing credit conditions on the TOM of a property. While the former capture the liquidity available on the market and account for the presence of financial constraints, the latter contains important information on a property's liquidity (marketability) and can be considered a proxy for matching frictions among potential buyers and sellers. Household credit frictions (i.e. a worsening in mortgage accessibility) can reduce the number of potential buyers that can afford a house, leading to a negative impact on the matching process and eventually to a lengthening of the time needed to sell a house.

The analysis and short-term monitoring of housing sector conditions is particularly important. First, construction is one of the most important sectors, and changes in housing market conditions can have considerable effects on the rest of the economy. Second, housing usually represents the biggest purchase for households and, consequently, any changes in a property's marketability can have significant effects on households' wealth and consumption.

The existing literature on housing (e.g. Yang and Yavas, 1995; Knight, 2002; and Anglin et al., 2003) shows that the TOM of a real estate property (residential as well as commercial) can be influenced by various factors. These include house listings and selling prices, the individual features of potential buyers and sellers (e.g. their wealth and credit availability) and of the properties on sale (quality, location and so on) as well as market peculiarities, brokers' incentives and macroeconomic conditions. However, the empirical evidence on the effect of such factors on TOM provides discordant results. This is mainly due to scarce information concerning housing market transactions at micro level. Furthermore, while the focus of most research on the housing sector has been on the causality effects between TOM and prices[1] there has been much less focus on the role of market liquidity and credit conditions in explaining TOM, especially on empirical grounds. This paper fills this gap by analysing the role of housing market liquidity as proxied by the loan-to-value ratio (LTV), in explaining the housing market's performance, proxied by the average Time on Market of

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[1] Laezer (1986) and Lippman and McCall (1986) provide models with different predictions of the effects of price changes on TOM.

properties. The LTV ratio is a very important indicator of the housing market; it provides information on the market credit conditions but also on the housing market response to the business cycle. The increase in mortgage value with respect to the house value is expected to increase the number of potential buyers that can afford a house and thus improve the matching process between buyers and sellers, resulting in a lower TOM. This relationship is studied, in addition to more traditional determinants (i.e. prices), using microdata at real estate agency level in a dynamic panel econometric model. It is important to notice that an easing in the housing credit accessibility represents a stimulus for the housing market. However from a macroprudential point of view an excessive increase of the LTV ratio is not always desirable due to a potential increase of systemic risks.

The empirical results of this article are based on a novel and unique proprietary dataset from the Bank of Italy housing market survey (HMS) that contains information provided by real estate agents on a wide set of indicators concerning the state of housing market.

The data coming from this survey display some shortcomings. For example, the information at agency level concerning the TOM, provided by real estate agents, is not referred to each single real estate transaction but is an average concerning all the transactions made by the agency in a given quarter. The same occurs for the other indicators collected from the survey (i.e. LTV ratios, price revisions) that are provided looking at all the transactions in a given quarter. Furthermore except for few indicators the majority of information collected is qualitative.

However, the main advantage of this survey (unique in Italy and also in Europe) is to collect the point of view on the housing market directly from the intermediaries that, working in the field, are able to capture the mood of the housing market evolution. Furthermore since information is collected at high frequency (on quarterly basis) provides updated signals concerning the "sentiment" of the housing market.

The period of analysis spans from 2011 to 2015 and covers the last part of the housing decline until the end of 2012, and the subsequent slight recovery.

Section 2 reviews the literature on housing market studies analysing the determinants of TOM. Section 3 describes the dataset. Section 4 reports the empirical results, followed by the conclusions.

2 The theoretical framework and the available studies

This paper is related to two main strands of literature on the housing market. Firstly it is linked to the studies that analyze, the relationship between price revisions, namely the difference between the initial listing price and final selling price, and TOM (Belkin Hampel and McLeavey, 1976; Anglin et al., 2003; Knight, 2002; Hoeberitchts et al., 2008). Secondly, the paper is related to the literature that inspects the role of credit frictions on the matching process between buyers and sellers (i.e. Ungerer, 2015; Eerola and Maattanen, 2015) and, more in general, to the papers focusing on the impact of the credit conditions on the housing market. Is important to notice that, although the debate concerning the interaction between credit market conditions and housing market is longstanding, there are no studies that analyze directly the relationships between TOM and credit conditions. The available studies are only limited to the analysis of the impact of changes in mortgages conditions on the house prices (see for example Krainer, 2010; Francke et al., 2014), on the impact of credit availability (proxied by LTV ratios, interest rates, etc.) on house prices (Zollino and Nobili, 2012; Kelly et al., 2017) or the interactions between property prices and credit cycle (Hofmann, 2003). No one of these papers analyzes data on LTV ratios at micro level.

The initial literature on TOM determinants in the housing market (both theoretical and empirical) focused on the relationship between selling prices and TOM (i.e. Lippman and Mc Call, 1986, Haurin, 1988) and between listing prices and TOM (Laezer, 1986; Yavas and Yang, 1995).

The list price (LP) of a property is the initial price at which the seller tries to sell a property (also called ask price) and can be revised according to market responses and according to sellers' 'attitudes to sell'. The selling price (SP) is the price at which the transaction is concluded and it is also called final price.

Concerning the linkages between SP and TOM, Lippman and McCall (1986) set up a search model that explains the price matching process between potential buyers and sellers. This kind of model postulates a positive relationship between selling prices and TOM; sellers willing to wait longer increase the probability of finding a buyer with a higher reservation price. Haurin (1988) provides an empirical application of search theory models to housing and finds a positive relationship of selling prices and TOM confirming Lippman and McCall (1986) model predictions.

A theoretical model analyzing the linkages between listing prices and TOM is instead Laezer (1986) two period model of pricing behavior under demand uncertainty. The model considers a stochastic arrival process of potential buyers while the seller is uncertain about the buyers price evaluation. There is a learning mechanism in the first period about buyers list price evaluation and thus in the second period list prices are lower than in the first period. The LP setting is clearly related to market thinness because if the seller receives few offers by the buyer, the initial

LP set by the seller is expected to be lower and the prices to decrease (see Wit and Klaauw, 2010). The model predicts that higher list prices revisions increase the TOM. In fact, while sellers wish to sell their homes at the highest possible price in the shortest possible period of time, buyers wish to buy houses at the lowest possible price in the shortest possible period of time. The Time on Market needed to sell will thus depend on the speed of the process that will lead to a convergence between LP and final SP.[2]

On the empirical side, the relationship between SP and LP differential (price revisions), and TOM has been widely investigated. The difference between LP and SP gives an indication of price revisions and thus can be considered as a spread measure of house prices. If listing price is set too high due to a pricing mistake by the seller then the likelihood of a buyer making an offer is lower than if the property was correctly priced. Consequently, the TOM will tend to be higher. Over time, the seller is likely to reduce the LP as TOM rises. Eventually the property sells but SP is lower than the initial LP. This is expected to result in a positive correlation of (LP-SP) and TOM.

The empirical evidence on the impact of price revisions on TOM has also been investigated but provides discordant results. For example Kang and Gardner (1989), using a single equation pooled model, find a significant and positive relationship between days on market of a house and the difference between listing prices and selling prices (used as an explanatory variable). In their view, a higher overpricing with respect to the final selling price thus determines a longer TOM of a property. Analogously Knight (2002) inspects the impact of changes in list price/selling price on TOM using least squares models and shows that homes where listing prices experimented a higher revision took longer time to sell.

Belkin, Hampel and McLeavy (1976), quite the opposite show that there is a negative relation between the ratio of the contract price (selling price) and the listing price and TOM.

Finally Jud et al. (1996) report no significant impact of price revisions on TOM while Ferreira and Sirmans (1989) find no impact of overpricing on TOM during periods of high interest rates.

This paper contributes to the above mentioned debate analyzing the impact of credit conditions on TOM, in addition to a number of control variables including also price revisions using microdata at agency level. An increase in the housing market credit availability is expected to improve the matching process in the housing market.

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[2] Due to the lack of data concerning price revisions, in many papers as an alternative, the speed of selling is put in relation to the final selling price or with the last list price so it is not possible to have information on price changes during the period in which a house is on the market.

3 The dataset and the measures of assets' liquidity and housing market liquidity

The data comes from the Bank of Italy survey among real-estate agentswho work on behalf of third parties[3]. The survey has been conducted on a quarterly basis since 1999 on roughly 1,200 agents per quarter and collects agents' opinions regarding the average Time on Market of houses, the pattern of house sales, price trends, opinions concerning housing credit conditions (i.e. average LTV ratios), expectations on potential buyers and sellers, the percentage of houses bought with a mortgage, general economic situation on the housing market and so on. The information collected is both quantitative and qualitative. Quantitative questions refer to the number of houses sold, the average TOM needed to sell properties, the number of houses bought using mortgages and LTV ratios. Qualitative questions concern housing market expectations, selling price expectations, and short- term and medium- term forecasts on the overall situation of the housing market and are processed by calculating the weighted difference between the percentage of positive and negative answers to a given question ('balances').[4]

All the information contained in the survey is provided at agency level and for this reason allows us to take into account the heterogeneity and variability of agents. With respect to other data sources that directly consider data concerning each specific transaction, in this kind of survey, all the indicators concerns an average assessment provided by estate agents on all the properties sold by an agency in a given quarter.[5]

The use of survey data ('soft data') to analyse the evolution of quantitative indicators clearly has some limitations compared with the use of quantitative information coming, for example, from national accounts data ('hard data'). First, the information does not refer to the whole population[6] and second, survey data are based on the respondents' opinions on a given phenomenon and, therefore, the answers provided are subjective. However, soft data have the advantage of being promptly available, not subject to revisions as in case of other data sources, and are often the only source of information available to investigate a given phenomenon.

The dependent variable analysed in our model is the average Time on Market of a house (TOM). This gives the average time in months needed to sell a property from the beginning of mandates to the agency as declared by real estate agents. The variable is an average because the agents are asked

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[3] For a detailed description of the survey methodology see Bank of Italy (2017).
[4] More in detail, the balance is expressed as B=100(P-N)*w where w is the weight of the agency equal to the inverse of the inclusion probability of a given agency in the sample, P are the positive answers and N the negative ones.
[5] The use of answers based on an 'average type or the most representative typology' of house, can, to some extent, provide measurement errors on the information required by the survey. However, since the frequency of houses sold is concentrated between 2 and 3 houses, and since the type of houses sold depends on the strata in which the agency is located, the typology of sold houses can be considered as quite homogeneous for a given agency.
[6] We consider only the housing market transactions based on intermediaries.

to provide an average time in months elapsed from the beginning of the mandate to the selling period for all the properties sold in the reference quarter.

As stated previously, this indicator is considered a proxy of the asset liquidity and also of the housing market health. In fact a lower time needed to sell a property indicates that the underlying real estate property can be more easily converted into cash and that the matching between buyers and sellers occurs in a faster way.

The dynamics of the average TOM for residential properties in Italy over the period 2009-2017 together with the median (P50), the 25th percentile (P25) and the 75th percentile (P75) are reported in figure 1.

Figure 1 Average Time on Market
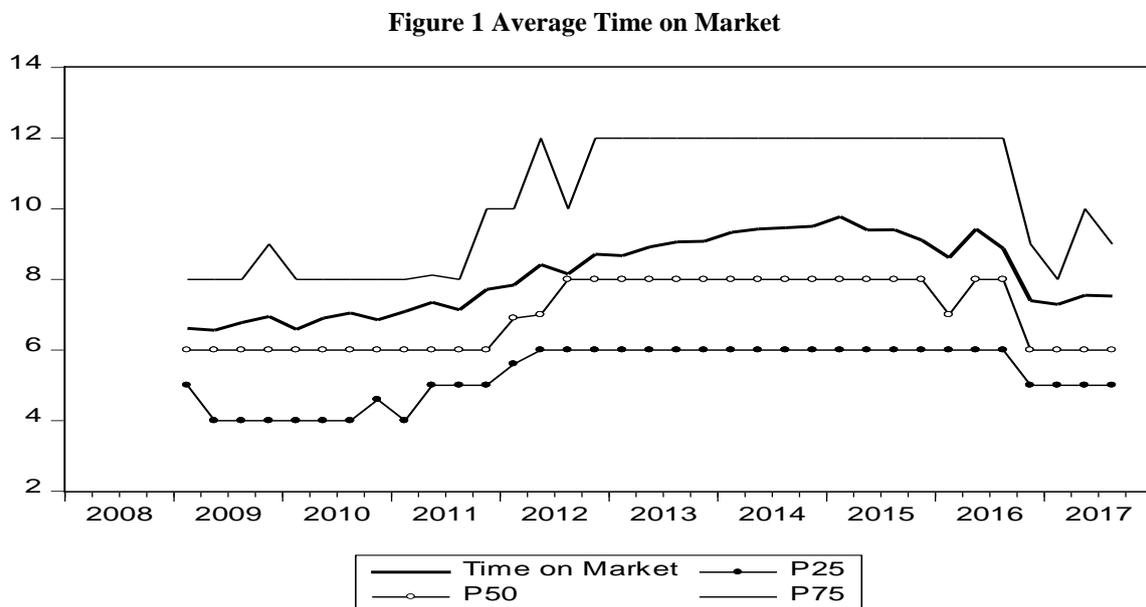
TOM displays a certain degree of persistence over time. After 2010, it experimented a significant increase and reached a maximum in the first quarter of 2015. After that date it started to decrease. The 2017 levels seem to be quite in line with the 2009 levels. The distribution of percentiles also show a variability of the phenomenon. In analyzing these data it is important to notice that a break in the series occurred in 2015 Q3 due to a change in the marketing company that is in charge for conducting the interviews. Moreover, since until 2010Q4 a lot of indicators are not available, we restrict our empirical analysis to the period 2011Q1-2015Q2.

As a check of the information coming from HMS, figure 2 reports a comparison of the average LTV ratio coming from HMS with the corresponding ratio coming from the Regional Bank

Lending Survey (RBLS)[7]. The RBLS survey is conducted twice a year, but the data on the LTV ratio from RBLS are collected once a year in the survey published in December with reference to the entire year.

Figure 2 Comparison between LTV ratio from Bank of Italy HMS and RBLS

Looking at the LTV from HMS we can notice that from 2010 it decreased by 14 points, according to the negative housing cycle phase, reaching a minimum in 2013, it began to increase from 2014 as a result of the recovery in housing market conditions. The LTV seems thus to follow the same dynamics of business cycle increasing during expansions and decreasing during recessions. Looking at the graph we can also note that, except for year 2013, the LTV from HMS is always higher than the one from the BLS survey, this difference in the levels of the two series is probably due to the fact that the LTV from HMS is referred only to houses transactions subject to a brokerage while BLS considers all property transactions. Furthermore, since LTV from HMS is observed by real estate agents it probably includes the real estate agent commission.

However, although the above mentioned differences between the two indicators, the analysis of the correlation over the period (equal to 0.70), shows similar dynamics between the two series.

Table 1 includes a complete description of the dataset used.

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7 The RBLS is conducted by the Bank of Italy and is addressed to the senior loan officers responsible for credit policies of roughly 300 banks. The questionnaire is similar to that one used for the bank lending survey that is conducted on quarterly basis by the national central banks of the countries that have adopted the single currency, in collaboration with the European Central Bank.

Table 1 Dataset description

TOM	It is the average time on months needed to sell a home from the beginning of the mandate observed by the agents. It is an average because the real estate agent consider the time observed on average looking at all the transactions observed during a given quarter. Available from 2009 Q1
AVPR	The average reduction is the percentage of price reduction obtained with the final price paid by the buyer in relation to the initial asking price of the seller. The indicator is an average because the agent gives a value considering all the transactions observed in a given quarter. This indicator gives an insight into the convergence dynamics for market clearing. In this sense this indicator represents a proxy of LP-SP variation (accounts for seller pricing strategies' effects on TOM). Available from 2009 Q1
MS	The number of mandates to sell at the end of the reference quarter compared with those in the previous quarter. The variable, representing a proxy of potential supply, is qualitative and built as a balance between increase and decrease of mandates to sell observed. It gives an indication of homes on the books still unsold at the end of the reference quarter. The variable is qualitative and built as a balance (proxy of mismatch between demand and supply). Available from 2008 Q4
PB qoq	Number of potential buyers in the current quarter (qoq). The agents give their opinion on the number of potential buyers in the reference quarter compared with the previous one. Since they are asked to give the percentage, the indicator is built as a balance and the indicators give an impression of the variation of potential buyers in the reference quarter compared with the previous one. It can be seen as a proxy of potential housing demand. (proxy of potential demand).This indicator is available from 2014 Q1
PB yoy	Number of potential buyers in the current quarter (yoy)The agents give their opinion on the number of potential buyers in the reference quarter compared with the corresponding quarter of the previous year. Since they are asked to give the percentage, the indicator is built as a balance. (proxy of potential demand).This indicator is available from 2014 Q1
HOUSESMORTG	This indicator gives the proportion in percentage of homes covered by a mortgage and sold in the reference quarter.
LTV_ratio	This indicator gives the proportion of the price of all homes covered by a mortgage and sold in the reference quarter.
AGTYPE	Agency type built as Dummy variable that is equal to 1 if the agency is in a group and 0 otherwise.
AGSIZE	This indicator gives the number of agents employed in a given agency.
HOUSESSOLD	This indicator is built as ratio of the number of houses sold by a given agency and the number of agents working in this agency. It is considered a measure of agency efficiency. It is obtained dividing the percentage of real estate agents that have sold at least one house in the reference quarter to the number of real estate agents that operate in each agency.
HM_SITGEN	It is the general situation of the housing market in the next three months and gives a short- term forecast on the housing market situation in the current quarter compared with the reference quarter. The variable is built as a balance.
AREAG4	This is the dummy for geographical areas. We assume that geographical areas (North West, North East, Center and South) account for possible spatial effects in explaining the speed of selling.
U_RATE	The unemployment rate at provincial level comes from the Italian Labour Force Survey conducted by ISTAT. The unemployment rate is calculated by expressing the number of unemployed persons as a percentage of the total number of persons in the labour force. The labour force is the sum of the persons employed and unemployed.

Overall, the housing market survey indicators collected from Bank of Italy HMS, used to analyse the interactions with the speed of selling, can be divided into two main groups:

Price information indicators: Price information included in the Bank of Italy survey concerns price revisions about houses sold observed by real estate agents over a given quarter, expectations regarding price dynamics in the next quarter or variability observed in rent prices.

Market structure indicators: this information accounts for the underlying market structure characterizing the environment in which the properties are sold. In this study the structure is determined by the actors such as potential buyers and sellers, as well as market liquidity conditions indicators (i.e. ease in obtaining a mortgage proxied by the LTV ratio and the number of houses bought with a mortgage) and agency efficiency indicators (based on the number of houses sold per agent and the size of the agency).

An increase of liquidity available in the housing market, proxied through an increase in the LTV ratio, is expected to increase the number of market actors that can afford a house and thus is expected to determine a TOM reduction due to the higher possibility to find a matching between buyers and sellers.

To provide an initial examination of the data, Table 2 reports some descriptive statistics concerning the housing survey indicators used in the empirical analysis over the whole period for which they are available.

Table 2 Descriptive statistics for housing market indicators. Period 2011Q1-2015Q2*

	Obs.	*mean*	*std. dev.*	*min*	*max*
Average TOM (months)	17142	8.21	5.09	1	90
no. of agents	26553	1.83	2.10	1	64
no. houses sold	8219	3.46	5.09	0	221
no. houses sold per agent	8150	0.29	0.89	0	15
Average price reduction % (LP-SP)	17248	15.0	8.37	0	35
Mandates to sell qoq	26075	3.29	0.87	1	5
New mandates to sell qoq	26047	3.17	0.86	1	5
Expected new mandates to sell qoq	26032	3.12	0.73	1	5
no. of potential buyers qoq	7028	1.92	0.73	1	3
no. of potential buyers yoy	6524	1.96	0.79	1	3
Percentage of Homes bought with a mortgage	14861	60.44	25.88	0	100
LTV ratio	13081	62.35	38.08	0	100
Gen. Housing mkt sit. 3m (wors./improvement)	25630	1.63	0.60	1	3
Gen. Housing mkt sit. 3y (wors./i improvement)	24510	2.08	0.82	1	3
Local Hosing mkt sit. (wors./ improvement)	26189	1.76	0.85	1	3
Unemployment rate	23011	11.42	5.05	3.19	25.68

*source: Bank of Italy housing market survey

On looking at the results we can note that while the average time to sell is roughly 8 months, it can range from a minimum of one month to a maximum of 7 years, displaying a high variability.

On average over the period, the percentage of mortgage value (LTV) compared to the house value is 62% while the percentage of houses bought requiring a bank loan is 61%. The agency dimension also shows a high variability ranging from a minimum of one person to a maximum of 64 agents while on average the number is 2 agents. The number of houses sold per agent is on average equal to 2 but goes from a minimum of 0 to a maximum of 15 houses in a quarter.

4 Empirical results

In this section I investigate the effects of housing credit conditions on the average time to sell a house. As a market liquidity indicator, I consider the loan- to- value ratio (LTV), namely the percentage of the property's value that is mortgaged.[8] In the model I also consider a set of control variables such as price revisions with respect to the initial listing price, market structure indicators (i.e. increase/decrease in potential buyers, increase/decrease in mandates to sell, role of brokers, geographical dummies). The dataset includes quarterly microdata at agency level from 2011 Q1 to 2015 Q2 and it is unbalanced because there are agencies in a given year that are not present in another year[9].

4.1 The empirical model

Since a preliminary analysis shows that TOM displays a certain degree of persistence, I model TOM using its lagged value in a dynamic panel setting. The general form of the equation is:

$$TOM_{it} = \beta_i + \beta_0 TOM_{i,t-1} + \beta_1 * LTV_{it-1} + \beta_2 * Z_t + e$$

where the dependent variable TOM_{it} is the average time needed to sell a house in months observed by real estate agent i at time t, LTV is a measure of housing credit conditions and Z_t is a set of control variables (i.e. price revisions, potential buyers and sellers, agency type, agency efficiency, geographical dummies).

In what follows the results of different dynamic panel regressions based on the Blundell Bond (1998) system GMM estimator are reported. The units are weighted to account for their different probability of selection. In all the regressions, endogenous regressors (i.e. the lagged dependent variable and the LTV ratio) were instrumented using their lags. Other instruments include explanatory variables such as, price revisions, geographical dummies, potential buyers and sellers. Exogenous instruments also include agency size, the number of transactions and the percentage of houses bought with a mortgage.

While the topic concerning the possible endogeneity of SP and TOM has been discussed in the literature (see Yavas and Yang, 1995; Waller, Brasow and Johnson, 2010; An Cheng Lin and

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[8] While the housing market credit conditions could also be captured by various financial indicators (i.e. interest rates), in this study I focus on LTV ratio because information is available at agency level and allows to capture eterogeneity among buyers.

[9]The unbalanced panel is due to the fact that in each survey there is a rotation of interviewed agencies. However roughly 85% of the sample is stable over time.

Liu, 2013) and it has usually been treated using two stages least squares[10], the endogeneity of price revisions with respect to the initial listing price is a more tricky and controversial question. In fact observed price revisions data (P_t –P_0) include a comparison between initial listing price set in the past (P_0) on which current TOM has clearly no role. In the paper I tested the possible endogeneity of price revisions using the Sargan test and they resulted exogenous[11]. Given the above mentioned results, in what follow I modelled price revisions, in the equation as exogenous instrument.

4.2 Baseline specification and robustness to different subsamples and subgroups

As an initial attempt, to assess the effects of liquidity changes on the Time on Market, table 3 reports a baseline specification (column 1) that considers as regressors the lagged level of TOM, the lagged level of the average LTV ratio estimated over the period 2011 Q1 -2015 Q2 on the whole sample of interviewed agents. To check the robustness of the results, column 2 reports the same specification of column 1 but considers the percentage of houses bought with mortgages as alternative measure of housing market credit conditions. Column 3 and 4 report a robustness check of the baseline specification based on two different types of agencies (i.e. independent ones vs. those associated with a group). This check allows us to test possible differences in the magnitude of LTV's impact due to the two subsamples. These two agency types can possibly experiment differences in terms of buyers characteristics, observed LTV ratios and houses attributes. For example agencies belonging to groups are expected to sell a higher percentage of luxury properties and to attract clients that are less financial constrained with respect to the average of potential buyers. Finally, in order to control for the role of different business cycle phases (i.e. expansions versus recessions) column 5 and 6 consider the baseline regression in two time subperiods: the business cycle recession phase until 2012 Q3 and the subsequent business cycle recovery phase from 2012 Q4 that also includes a recovery in housing market conditions. The turning point used to split the sample was detected using GDP data as well as other housing survey indicators concerning the general economic situation in the housing market coming from the housing survey.[12]

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[10]Through this technique the endogenous regressor in a OLS is proxied by an instrument that is not correlated with the error.

11The robustness of this modelling choice is also corroborated by the fact that including price revisions among the endogenous regressors the coefficient becomes insignificant.

12 Although the business cycle and the housing cycle can have different phases and turning points, they are related. Looking at GDP dynamics and general housing market condition indicator coming from the housing market survey, the 2012 downturn is the same for both cycles.

Looking at the results of model 1 we can see that the lagged value of TOM is positive and statistically significant, showing a significant degree of persistence. The LTV ratio regressor is negative and statistically significant: a higher LTV, increases house affordability, improves the matching between buyers and sellers and reduces the average TOM as expected.

Looking at model 2, we can observe that the alternative credit conditions measure, the number of houses bought with a mortgage, is not statistically significant. This finding is probably due to the fact that this alternative indicator, gives no information about the amount of liquidity observed and could not be able to capture changes in housing credit conditions. For example the indicator could increase without a corresponding increase of mortgage level as in the case of LTV ratio.

Table 3 Dependent variable: TOM in levels. Dynamic panel data estimation. Blundell Bond system GMM estimator. Weighted regression.**

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
	Baseline	*Alternative housing credit measure*	*Independent Agencies*	*Agencies Groups*	*Split sample 2011q1 2012q3*	*Split sample 2012q4- 2015q2*
Constant	7.25 (0.000)	5.39 (0.000)	7.66 (0.001)	-0.7 (0.449)	5.82 (0.006)	5.71 (0.008)
TOM (-1)	0.58 (0.000)	0.39 (0.000)	0.72 (0.000)	0.71 (0.000)	0.60 (0.000)	0.57 (0.000)
LTV ratio(-1)	-0.06 (0.013)	-----------	-0.09 (0.003)	0.07 (0.108)	-0.054 (0.042)	-0.063 (0.022)
HOUSEMORTG (-1)	-----------	-0.006 (0.686)	-----------	----------	----------	----------
Sargan test overid. restrictions	21.14 (0.133)	13.75 (0.469)	24.69 (0.055)	26.60 (0.032)	16.71 (0.117)	16.0 (0.141)
AR(1)	-7.15 (0.000)	-6.12 (0.000)	-6.49 (0.000)	-5.73 (0.000)	-5.98 (0.000)	-5.54 (0.000)
AR(2)	0.66 (0.510)	2.27 (0.023)	0.41 (0.685)	2.29 (0.022)	-0.23 (0.819)	-0.22 (0.826)
No of instruments	21	20	21	21	17	17
No. of observations	9083	10179	7264	1735	6220	5836
Number of groups	2144	2232	1830	443	1723	1682
Wald Chi square test	107.20 (0.000)	75.23 (0.000)	67.27 (0.000)	61.51 (0.000)	77.98 (0.000)	76.18 (0.000)

*p-values in parenthesis **weights are given by the inverse of the sample probability of each unit.
Notes: LTV ratio: Loan To Value ratio.
HOUSEMORTG: Percentage of houses bought with a mortgage.

The results of models 3 and 4 considering agency type subsets, show that the LTV ratio is significant and displays a negative effect on TOM for the panel of brokers operating in independent agencies while the same relation is not statistically significant for the agencies belonging to a group. This result seems to show that buyers turning to small agencies are credit-constrained, while this is not true for buyers turning to agency groups. This explanation is corroborated by the evidence from

previous information in the housing survey showing that agency groups usually deal with properties with a larger surface area, measured in square metres. This type of home is bought by clients that are presumed to be less financially constrained.

Regressions reported in Models 5 and 6 check the robustness of the baseline specification with respect to the two different business cycle phases (recession and recovery). The results show that the LTV ratio displays the same magnitude in its coefficient on TOM in both subperiods (recession and subsequent recovery) showing that market liquidity changes account for different business cycle conditions. In all six models considered, robustness' control for geographical dummies show in most cases no significant local effects.[13]

To quantify the impact of housing market credit conditions on TOM, table 4 reports, the long-term impact of the estimated LTV ratio coefficients on TOM.[14] To perform the impact exercise I consider the regression coefficients reported in Table 3.

Table 4 TOM long run impact coefficients

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Alternative credit measure	Independent Agencies	Agencies Groups	Split sample 2011q1 2012q3	Split sample 2012q4- 2015q2
LTV ratio (-1)	-0.13	-----	-0.32	0.23	-0.12	-0.14
HOUSEMORTG (-1)	-----	-0.009	-----	-----	-----	-----

The coefficient of the long-run impact on TOM of LTV in the baseline equation is -0.13: an increase by one percentage point in the LTV ratio determines, in the long run, a decrease of 0.13 months in the TOM. Ceteris paribus, the sharp fall in the LTV ratio between 2010 and 2014 (14 percentage points) as measured in the HMS raised by less than two months the time needed to sell as a property. For the subsample of independent agencies, the LTV long run coefficient doubles to -0.32 determining a decrease of 0.3 months in TOM when LTV increases of one percent point while for the group agencies the coefficient is not significant. Over the two business cycle phases considered the long run impact coefficient is more or less the same. All in all, in order to have a decrease of one month in the TOM the LTV ratio should increase by 8 percentage points.

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[13] The results are not reported for brevity reasons.

[14] We obtained estimates of long-run effects by applying the following transformation: B2 long run = B2/(1-B1), where B2 is the coefficient of the regressor and B1 is the coefficients of the lagged dependent variable.

4.3 Robustness with respect to different control variables from market structure

The wealth of information contained in the dataset at agency level makes it possible to check the robustness of the results with respect to the inclusions of key indicators concerning the market structure (i.e. potential buyers, mandates to sell, agency size, agency type[15] and agency efficiency) in explaining the TOM of a property. Potential buyers and mandates to sell indicators account for changes in potential demand and supply observed by the agents. Since these indicators are collected in the form of balances, they are modeled as dummies (i.e. a dummy accounting for positive answers, namely an increase, versus a dummy accounting for negative ones, namely a decrease/reduction).

The agency size, agency type and agency efficiency indicators account for the role of brokers in the matching process of the house search. There is a link between the performance of the broker and the time a house remains on the market that will be reflected in a higher probability to find a matching between buyers and sellers. Greater agency efficiency (resulting in a greater number of houses sold per agent) is expected to improve the matching process between buyers and seller and will be reflected in a shorter time needed to sell.

The role of agencies in the matching process has been explored in various works. Jud, Seaks and Winkler (1996) consider the role played by the agencies on TOM by analysing the impact of brokerage firms and agents' characteristics. In their findings there is no agency type role in reducing the time needed to sell a property; the dissemination of information would be available to both buyers and sellers through multiple listing services[16], and would not depend on the agency type. Analogously Waller et al. (2010) consider the role of real estate agent and analyse the relationship between the agency contract length and TOM, and find evidence of a decrease in an agent's incentive to sell as the contract length increases. This produces a higher selling time of the property. In this case too there are no studies explicitly focusing on agency efficiency. To test the possible role of market structure on TOM, in the regressions reported in table 5 I consider six specifications.

Model 7 of table 5 regresses TOM on its lag, the lag of the LTV and on the average price revisions (AVR) observed by the real estate agents. The indicator is built considering the revision observed in the final selling price with respect to the initial listing price. Model 8 of table 5 regresses TOM on its lag, the lag of the LTV ratio and a '*dummy mandate to sell*' accounting for changes in the mandates to sell, used as a proxy of housing supply, in the current quarter with respect to the previous one. More in detail I consider a dummy for mandate decreases (D_RMS)

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[15] Independent agencies versus group agencies.

[16] A multiple listing service (MLS, also multiple listing system or multiple listings service) is a suite of services that real estate brokers use to establish contractual offers of compensation (among brokers) and accumulate and disseminate information to enable appraisals.

and a dummy for mandate increases (D_IMS). Model 9 regresses TOM on its lag and the LTV ratio but includes a dummy that considers the effects of changes in the number of potential buyers (decreases versus increases) with respect to the previous year (D_RPB and D_IPB) that is considered as a proxy of potential demand. Model 10 considers the baseline specification augmented with a measure of the agency efficiency (i.e. number of houses sold per agent), a dummy (AGTYPE) accounting for agency structure (i.e. independent agencies versus groups) while model 11 adds the agency size indicator (AGSIZE) as further control. Model 12 considers the unemployment rate (U_RATE) by province coming from the Italian labour force survey as further control. We expect that un increase in the unemployment rate, capturing a worsening in the individuals economic conditions, will be associated to a higher TOM.

Table 5 Dependent variable: TOM in levels. Dynamic panel data estimation. Blundell Bond System GMM estimator. Weighted regression.

	(7)	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
	Baseline augm. with price revisions	*Baseline augm. with supply conditions*	*Baseline augm. with demand conditions*	*Baseline augmented with an efficiency indicator and agency type dummy*	*Baseline augmented with an efficiency indicator, agency type dummy and agency size*	*Baseline augmented with provincial unemployment rate*
Constant	6.34 (0.001)	6.3 (0.001)	6.36 (0.001)	11.14 (0.000)	11.51 (0.000)	9.92 (0.000)
TOM (-1)	0.55 (0.000)	0.55 (0.000)	0.54 (0.000)	-0.39 (0.025)	-0.40 (0.000)	-0.23 (0.155)
LTV(-1)	-0.06 (0.006)	-0.064 (0.006)	-0.060 (0.006)	-0.015 (0.001)	-0.014 (0.001)	-0.08 (0.002)
AVPR	0.08 (0.000)	0.08 (0.000)	0.08 (0.000)	0.15 (0.000)	0.15 (0.000)	0.12 (0.000)
D_RMS	----------	0.09 (0.557)	-----------	--------	---------	---------
D_IMS	----------	0.21 (0.055)	-----------	---------	---------	---------
D_RPB	----------	----------	-0.52 (0.016)	----------	---------	---------
D_IPB	----------	----------	0.03 (0.873)	-------	---------	---------
HOUSESSOLD	----------	----------	-----------	-0.18 (0.000)	-0.19 (0.018)	---------
AGTYPE	----------	----------	----------	-1.30 (0.000)	-1.09 (0.000)	---------
AGSIZE	----------	----------	----------	----------	-0.20 (0.000)	---------
U_RATE	----------	----------	----------	----------	----------	0.11 (0.000)
Sargan test	21.45 (0.123)	21.78 (0.114)	21.44 (0.123)	1037.04 (0.000)	1021.76 (0.000)	32.48 (0.003)
AR(1)	-7.35 (0.000)	-7.36 (0.000)	-7.31 (0.000)	-0.92 (0.355)	-0.94 (0.346)	-2.97 (0.003)
AR(2)	0.65 (0.517)	0.60 (0.549)	0.64 (0.523)	-1.40 (0.162)	-1.42 (0.155)	-0.25 (0.801)
No. of instruments	22	24	24	108	109	22
No. of observations	8946	8854	8946	4229	4195	6271
Number of groups	2123	2110	2123	1462	1456	1580
Wald test	409.36 (0.000)	414.29 (0.000)	429.74 (0.000)	1123.34 (0.000)	1201.48 (0.000)	917.62 (0.000)

*p-values in parenthesis **weights are given by the inverse of the sample probability of each unit.
Notes: LTV ratio: Loan To Value ratio
AVPR: Average price reduction
D_RMS: Dummy for reduction in Mandates to sell (qoq)
D_IMS: Dummy for increase in Mandates to sell (qoq)
D_RPB: Dummy for reduction in Number of potential buyers (yoy)
D_IPB : Dummy for increase in Number of potential buyers (yoy)
HOUSESSOLD: No. of houses_sold_per_agent
AGTYPE: Agency type (1=independent agency, 0= group agency).
AGSIZE: Size of Agency
U_RATE: Unemployment rate

The results of model 7 including price revisions information show that the sign of LTV is robust with respect to the previous specifications, the results also show that the average price reduction coefficient (AVPR) is positive and statistically significant.

The results of model 8 indicate that even in this case the LTV ratio is significant and enters the regression with the expected negative sign. The dummy accounting for a decrease in the mandates to sell (D_RMS) is not significant. On the contrary, an increase in the number of mandates to sell with respect to the previous years (D_IMS) is significant and contributes to increasing the TOM.

The results from model 9 indicate that the LTV ratio coefficient is negative and statistically significant, showing an effect on TOM similar to model 8. The results also indicate that only the dummy for a reduction in the number of potential buyers is statistically significant and the TOM of a property increases as expected. An increase in the number of potential buyers is not statistically significant.

Results from model 10 show that both LTV and the number of houses per agent (accounting for the role played by agency efficiency) enter with the expected negative sign and both of them contribute to lowering TOM. The results confirm our prediction: the higher the ability of intermediaries, the more we will expect to find a matching in the search process of a house.

The results from dummy accounting for agency structure (AGTYPE) show that in case of mandate to single agencies the TOM experiments a further reduction. This result is in contrast with Jud, Seaks and Winkler (1996) findings of no role of agency type on TOM. Model 11 adds the size of agency (AGSIZE), given by the number agents in each agency, as control. The coefficient is positive and statistically significant. The results thus indicate, as expected, that a greater agency size is associated to a lower average TOM of residential properties.[17] Finally model 12 adds the unemployment rate by province used as control. The results show that the coefficient is positive and statistically significant, as expected a higher unemployment rate contributes to increase the TOM. LTV and price revisions are also in this case statistically significant.

4.4 Overall Findings

The results from empirical analysis show that overall, credit changes in the housing market can have an influence on the housing market matching process between buyers and seller. Summarizing the main evidence of this research we can report the following main findings:

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[17] As further robustness check we estimated all the equations of table 4 with price revision and we found robust results The effect of the price changes (namely the average price reduction with respect to the initial price) declared by real estate agents on TOM in all cases is positive and significant.

Result 1. An improvement in the housing market liquidity conditions, captured by an increase in the LTV Ratio reduces the selling time of a property.

Result 2. Overpriced properties increase the selling time.

Result 3 An increase in agency efficiency reduces the selling time of a property.

Result 1 shows that an improvement in household leverage, proxied by the LTV ratio, can improve overall housing market liquidity. Better mortgage conditions can encourage potential buyers to enter the market. An improvement in credit conditions can reduce matching frictions, thus leading to a shorter TOM.

Our findings also provided additional evidence on the effects of price revisions on TOM (Result 2). Greater changes in final price revisions with respect to the initial listing price are associated with an increase in the time to sell a property. Overpriced properties experience in this sense a longer time in which the property remains on the market.

Result 3 shows that an increase in agency efficiency - measured by the number of houses sold per agent – is found to be significant and also contributes to a shorter TOM. The latter result confirms the role of brokers in the matching improvement.

5 Conclusions

The monitoring of the Italian housing market situation has received a lot of attention especially after the global financial crisis. One way to look at the market real estate evolution and its health over time is by considering the Time on Market of a property (TOM). Indeed TOM is a key health indicator of the housing sector as it represents a proxy of the underlying real estate asset liquidity.

Since asset liquidity clearly depends on the liquidity available in the housing market,[18] this paper investigates the effects of housing credit conditions on the TOM of a property by using a unique dataset from a survey of real estate agents with regard to the Italian residential housing sector. This survey captures the sentiment of the housing sector (i.e. expectations for the overall market situation) as well as more specific information concerning the number of houses sold, TOM, price variations, mandates to sell, potential buyers and mortgages. The analysis, based on a dynamic panel model in order to account for the persistency of TOM, allows us to examine the effect of credit conditions on TOM by using comprehensive and consistent data at agency level. The wealth

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[18] A higher market liquidity is expected to lead to a lower TOM due to an increase in a house's affordability.

of the information included in the data, has also allowed us to test various hypotheses concerning competing economic theories on the impact of housing market conditions on TOM, such as the impact of price revisions and the role of brokers.

The empirical analysis highlights three main results. In our findings, an increase in the LTV ratio produces a reduction in the average TOM of a property. A higher housing market liquidity, by increasing the number of potential buyers in the market, contributes to simplifying the matching process between buyers and sellers, leading to a lower TOM. A robustness check shows that the above findings hold with respect to different econometric specifications and control variables (i.e. potential buyers and sellers, and geographical dummies). On the basis of the analysis of long run impact coefficients, the very large fall by 14 percentage points in the LTV ratio between 2010 and 2014, if permanent, would have lengthened the time needed to sell as a property by less than 2 months.

The results of this study also indicate that greater changes in final price revisions with respect to the initial asking price lead to an increase in the time to sell a property. These findings are in line with Kang and Gardner's (1989) and Knight's (2002) results and confirm that an initial overpricing, possibly due to a mispricing of the seller when setting the initial list price, but also interpretable as a signal of market thickness, produces an increase in the bid process time among buyers and sellers.

The paper also tests the role of brokers in the matching process between buyers and sellers. The results show that greater agency efficiency – measured by the number of houses sold per agent – leads to a lower TOM. This finding shows that mismatching among market players can partly be resolved by a greater efficiency on the part of intermediaries.

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