Price Dispersion and Frictions in the Physical Capital Market*

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Abstract

We study the market valuation of physical capital and the frictions associated with its trading. Using a unique dataset on a panel of nonresidential structures listed for trade, we document a large degree of price differences that cannot be explained by the rich set of characteristics included in the listings. We also show that listings with high price relative to their listed characteristics have systematically higher expected returns, but longer expected durations. We analyze the empirical support for alternative theories explaining these facts and find that the data patterns are consistent with theories of frictional trading with asymmetric information in capital quality. We use this environment, together with our empirical evidence, to quantify the implications of these frictions for investment inefficiencies and misallocation.

Keywords: Capital market, price dispersion, asymmetric information, trading frictions, investment, fire sales, misallocation.

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1 Introduction

The process through which physical capital is traded has important implications in macroeconomics and finance, impacting firms’ investment decisions, collateral values in financial contracts, and the efficiency of capital allocation in the economy. We study the trading process of physical capital by documenting key empirical patterns of market prices and liquidity in the microdata. We show that our empirical findings are consistent with theories of frictional trading with asymmetric information and study their implications for investment inefficiencies, fire sales, borrowing costs, and misallocation.

We use a dataset that allows us to construct a novel joint measurement of individual market prices and liquidity of capital units listed for trade. In particular, our dataset contains the history of nonresidential structures (retail and office space) listed for rent and sell in Spain from one of Europe’s main online real estate platforms, Idealista, with rich information on each unit, including the listed price, the exact location, size, age, and other characteristics. Given the data’s panel structure, for each unit we can compute the duration in the platform and the search intensity received, measured by the number of clicks received in a given month.

Using these data, we document three facts about prices and liquidity of capital goods. First, we show a significant degree of price differences that cannot be explained by individual characteristics included in the listing. For instance, the interquartile range in log prices within units listed in the same time period—in the same neighborhood and with similar size, age, and other characteristics—is 30%. To put this figure into perspective, we note that this magnitude is similar to the average contraction in capital prices observed during the Great Recession in our sample. Given how narrow the comparison is in terms of observable characteristics (which explain 70% of the variation across prices), we refer to price differences not explained by observable characteristics as price dispersion.

Our second fact is that these price differences matter for trading. Listings with a high residual price (i.e., with a high price relative to its listed characteristics) tend to have a longer duration and lower search intensity than listings with a low residual price. This is a tight relationship, which is in sharp contrast with that observed for predicted prices (i.e., the component of prices explained by observable characteristics). In particular, when a unit of capital is expensive because of its observable characteristics, it tends to have a shorter duration and higher search intensity; when it is expensive beyond its observable characteristics, it tends to have longer durations and less search intensity. Finally, we document that units with high residual price tend to have systematically

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1Our use of the term price dispersion is similar to the use of the term wage dispersion in the labor-market literature, which is used to denote wage difference in workers with similar observable characteristics (see, for example, Mortensen, 2005). This use of the term is broader than its use in the goods market, in which data is available for exactly identical goods.
higher expected returns for all possible ranges of seller discount factor and risk aversion, implying that the relationship between residual prices and duration is not steep enough to make sellers indifferent in the price-duration trade-off.

The central question emerging from these facts is: What drives price and return differences beyond observable characteristics? We show that our empirical findings are consistent with models of asymmetric information and search frictions in capital markets in the tradition of Guerrieri et al. (2010). We show that, in these models, asymmetric information in capital quality can lead agents who own high-quality capital to signal their type by choosing to list capital at high prices, which are visited less frequently by buyers and have lower matching rates. As sellers of low-quality capital have a higher marginal cost of not selling the capital unit, they choose not to mimic the high type (which is similar in spirit to the low type with a higher marginal cost of effort in the classical model of Spence, 1973). This can rationalize the findings in the data that capital units with high residual prices have longer expected durations and lower search intensities. The model also predicts that, in the absence of asymmetric information, capital of higher quality tends to have a higher price and to match at higher rates, as observed in the relationship between the component of prices explained by observable characteristics and duration. We provide evidence supporting the explanation based on asymmetric information by documenting a higher price dispersion in older capital units (a proxy often used to measure a high degree of uncertainty in the quality of capital), and that the relationship between residual prices and duration is steeper for older units.

We also show how it would be hard to rationalize our empirical findings with other key theories that have been used in the literature of price dispersion in labor and goods markets. In the first place, our empirical finding that units with higher residual prices tend to have higher expected returns challenges an explanation of price dispersion in capital prices based on sellers’ indifference about the trade-off between price and time to sell (e.g., Burdett and Judd, 1983). Given that these returns are higher even for a discount factor of zero and for the worst possible realization of duration associated with a price residual, the empirical patterns also challenge explanations based on seller heterogeneity in discount factors or risk aversion. In addition, we show that the dispersion of returns does not correlate with business cycles, challenging an explanation of price dispersion based on heterogeneity in sellers’ marginal utilities of consumption. Finally, we show that, in a given period, the price dispersion for new listings is similar to the price dispersion of existing listings, challenging a possible explanation of price dispersion based on costly price adjustment.

Informational frictions in our model have important policy implications, which we quantify using a model with frictional trading and asymmetric information disciplined by our empirical findings. First, these frictions lead to capital misallocation, as high-quality capital is matched less
frequently. The government can improve efficiency by taxing capital units traded at higher prices, and decreasing the degree to which the high type must increase the price to signal its type. Second, informational frictions lead to inefficient fire sales. If the owner of a high-quality unit wants to liquidate her capital, she pays a cost associated with the fact that the market interprets the choice for higher trading probabilities as a signal of lower quality. Our results have broader implications. In particular, they imply that taxing capital units traded at higher prices might not only improve the allocation of capital, but also reduce deadweight losses from default in debt contracts and firms' borrowing costs.

**Related Literature** Our paper contributes to several branches of the literature. First, in the literature using microdata to study trading frictions in the capital market, key contributions include Ramey and Shapiro (2001), who document prolonged selling times for closing aerospace plants, and Gavazza (2011), who shows that thinner markets are less liquid, have lower prices, and show higher price dispersion. We complement these findings with empirical facts relating individual capital units' prices to their liquidity and search intensity. These facts, in turn, allow us to show how asymmetric information can be a key friction for the trade of physical capital.

Second, our paper contributes to the theoretical literature on asymmetric information and search frictions pioneered by Guerrieri et al. (2010) and further studied in Delacroix and Shi (2013), Guerrieri and Shimer (2014), and Lester et al. (2018), among others. Our paper contributes to this literature by providing the first empirical support to these theories for the physical-capital markets.²

Third, our paper contributes to the large body of research measuring resource misallocation (see, for example, Hsieh and Klenow, 2009). We contribute to this literature by studying a novel form of misallocation stemming from agents that own high-quality capital signaling their type by choosing to list capital at high prices, which are visited less frequently by buyers and have lower matching rates. This form of misallocation would typically not be measured among existing firms, but rather among unemployed capital.

Fourth, our empirical work is similar in spirit to papers that have documented relevant facts about prices (see, for example, Bils and Klenow, 2004; Nakamura and Steinsson, 2008; Kaplan and Menzio, 2015) and wages (see Mortensen, 2005, and references therein). We contribute to this literature by documenting empirical patterns in prices of capital goods. This evidence is important because it can be linked to large classes of investment models with trading frictions in the physical

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²For empirical studies of asymmetric information in the insurance and financial markets, see Chiappori and Salanie (2000), Ivashina (2009), and Einav et al. (2010), among others. See Kurlat and Stroebel (2015) for evidence of asymmetric information in housing markets.
Finally, our paper contributes to the literature on capital reallocation. Empirical studies have shown that capital reallocation is large and procyclical (see, for example, Ramey and Shapiro, 1998; Eisfeldt and Rampini, 2006; Eisfeldt and Shi, 2018, and references therein). We contribute to this literature showing how asymmetric information can increase the duration of the reallocation process, leading to a potential scope of Pareto-improving market interventions. In this literature, our work is also related to studies in secondary markets, where arguably the consequences of asymmetric information can be more severe.\footnote{For example, the evidence presented in this paper can be linked to models with asymmetric information in the physical-capital market, such as Eisfeldt (2004), Kurlat (2013), and Bigio (2015); models with search frictions in the physical-capital market, such as Kurmann and Petrosky-Nadeau (2007), Cao and Shi (2017), Ottonello (2017), Kurmann and Rabinovich (2018), and Hormer (2018); models with irreversibilities, such as Bertola and Caballero (1994), Abel and Eberly (1996), and Veracierto (2002); and models with capital specificity, such as Caballero and Hammour (1998) and Altig et al. (2011). More broadly, the evidence in the paper can also be linked to models with search frictions in financial markets (for a recent survey, see Lagos et al., 2017) and housing markets (see, for example, Wheaton, 1990; Krainer, 2001; Caplin and Leahy, 2011; Piazzesi et al., 2015).}

**Layout** The rest of the paper is organized as follows. Section 2 presents the data. Section 3 documents facts about prices and liquidity of capital goods. Section 4 presents the model with frictional trade in the capital market to explain price dispersion. Section 5 maps the model to the data and quantifies informational asymmetries and policies. Section 6 concludes.

## 2 The Data

Our data consists of a panel of nonresidential structures (retail and office) posted for sale and rent. The source of these data is **Idealista**, one of Europe’s main online real estate intermediaries.\footnote{Idealista is the leading online platform in the real estate market in Spain (see Comparison of users and Comparison of platform).} The dataset includes roughly 3 million observations for Spain, where an observation corresponds to a property–date pair. These observations come from over 350 thousand different capital units, the universe of listings in this platform, listed between 2005 and 2013.

Our main variable of interest for each capital unit is its price, which we observe for each property at a monthly frequency. Table 1 shows the mean price for the different types of properties. The average sale price per square foot is $170 for retail and $253 for offices. Monthly rents are around one dollar per square foot per month.

For each property, we observe a wide range of characteristics that we link to its price. In particular, we observe the exact address of the property, its age, its area, whether it is in a good

\footnote{Other papers have explored additional implications of secondary asset markets. See for example, Lanteri (2018) for endogenous irreversibility and Gavazza and Lanteri (2018) for endogenous illiquidity.}

\footnote{Other papers in the literature have made use of data from online platforms in the real estate market (see for example (Piazzesi et al., 2015)).}
Table 1: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Retail Sale</th>
<th>Office Sale</th>
<th>Retail Rent</th>
<th>Office Rent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>198.05</td>
<td>294.88</td>
<td>1.11</td>
<td>1.28</td>
</tr>
<tr>
<td>Age</td>
<td>20.41</td>
<td>22.59</td>
<td>20.65</td>
<td>24.77</td>
</tr>
<tr>
<td>Area</td>
<td>3.594</td>
<td>2.485</td>
<td>3.219</td>
<td>2.500</td>
</tr>
<tr>
<td>Ground level</td>
<td>0.70</td>
<td>0.00</td>
<td>0.83</td>
<td>0.00</td>
</tr>
<tr>
<td>Heat</td>
<td>0.24</td>
<td>0.52</td>
<td>0.27</td>
<td>0.57</td>
</tr>
<tr>
<td>Rooms</td>
<td>1.93</td>
<td>3.25</td>
<td>1.79</td>
<td>3.11</td>
</tr>
<tr>
<td>AC</td>
<td>0.30</td>
<td>0.57</td>
<td>0.38</td>
<td>0.66</td>
</tr>
<tr>
<td>Clicks</td>
<td>11.46</td>
<td>11.49</td>
<td>14.07</td>
<td>16.11</td>
</tr>
<tr>
<td>Duration</td>
<td>10.18</td>
<td>11.21</td>
<td>8.13</td>
<td>9.27</td>
</tr>
<tr>
<td>Observations</td>
<td>1,010,074</td>
<td>251,363</td>
<td>1,039,913</td>
<td>689,132</td>
</tr>
</tbody>
</table>

Note: The four columns report different types of property and operations. Price denotes the mean price listed, expressed in constant 2017 dollars per square foot for sales, and dollars per square foot per month for rentals. Age is in years, Area in square feet, ground level is a categorical value that takes the value of one if the property is at ground level, Heat and AC are categorical variables that take the value of one if the property has heating and air conditioning, respectively. Rooms is the number of separate rooms of the property. Observations denotes the number of property–month pair observations we have available in the dataset for each type of property.

condition, the year in which the property was built, whether the property is located in a commercial complex, the number of rooms, and whether the property has heat or air conditioning. Table 1 presents some descriptive statistics on these characteristics. The properties are relatively old, with the average age around 20 years. The properties have similar sizes for a given type regardless of the operation. Most of the retail spaces are located at the ground level, but no offices are.

For each capital unit, we also observe two key variables related to its time-to-sell and the attention it receives in the platform. First, based on the identifier of each property, we compute the number of months the unit is listed in the platform, which we refer to as duration. Table 1 shows that units remain in the platform between eight and 11 months on average. Second, we compute each capital unit’s search volume in each month, measured by the number of clicks that a potential buyer gives to the unit to look at its details. Each unit receives between 10 and 15 clicks per month. On top of that, we observe the number of inquiry emails that each property receives per month.

Appendix A provides more details about the dataset. In particular, Section A.1 presents an introduction to how the online platform works. Section A.2 studies the representativeness of the dataset, showing that the dataset is consistent with aggregate patterns observed in Spain during the period of analysis in terms of the aggregate evolution of prices and the timing of sales.

3 Facts About Prices and Liquidity

In this section, we present three new sets of facts about prices and liquidity of capital goods. The first set documents to what extent differences in capital prices can be explained by observable
characteristics. The other two guide theories on why similar capital units have different prices, focusing on the relationships between prices, time-to-sell, and search and on the presence of price stickiness.

3.1 Facts 1: Price Dispersion

We begin by documenting three facts about price dispersion in the physical capital market: (i) a large heterogeneity in prices of capital units posted in the market to be traded, (ii) a considerable share of price differences not explained by characteristics included in the listings (20%–30%), and (iii) most price dispersion explained by time-invariant characteristics of the unit posted.

(i) Heterogeneity in posted prices  Figure 1 depicts the distribution of posted prices for sale and rent, pooled over the entire sample (expressed in constant 2000 dollars per square foot). The average price, depicted with the dashed line in each panel, is around $130 per square for sales and $0.60 per square foot per month for rent. The distribution is right-skewed and shows a wide range of prices posted. For instance, it is not unusual to find properties with prices at or greater than twice the mean. The interquartile range (IQR) of log prices is 72% for sales and 79% for rentals.

(ii) Price variation explained by listed characteristics  We study the role of different observable characteristics, included in the listings, to account for variation in capital prices.

The first key observable dimension explaining differences in capital prices is location, which naturally plays an important role in the case of structures. Figure 2 shows remarkable differences in sale prices across regions at different levels of aggregation. Panel (a) shows the average price...
across the fifty provinces in Spain; Panel (b) zooms in to the province of Madrid and shows the average price across municipalities in that province; Panel (c) zooms in the city of Madrid and shows the average price across neighborhoods in the city. These maps illustrate that locations vary significantly in their capital prices. To quantify the role of location driving differences in capital prices, we estimate a model of log prices on regional fixed effects: \( \log(q_{ijt}) = \alpha_j + \varepsilon_{ijt} \), where \( q_{ijt} \) is the price of capital unit \( i \) in location \( j \) in period \( t \), \( \alpha_j \) are location fixed effects, and \( \varepsilon_{ijt} \) is a random error term. Location fixed effects are defined, for each unit, at the finest geographical level possible in the platform: the neighborhood level in the case of big cities like Madrid or Barcelona and the city level in smaller cities. Results are similar if we focus only on cities that have available neighborhood information. Table 2 presents the results of this exercise, showing the \( R^2 \) of the fixed-effect regression and the IQR of residual prices. In this model, location explains almost 50% of the variation in prices.

**Figure 2: Capital Prices Across Locations**

(A) Spain

(B) Province of Madrid

(C) City of Madrid

*Note: Each map shows average prices by location expressed in constant 2000 dollars per square foot. The top panel shows average prices across provinces in Spain. The lower-left panel zooms in to the province of Madrid to show substantial heterogeneity across municipalities within this province. The lower-right map shows that, after zooming in the municipality of Madrid, there is still significant geographical dispersion of prices across neighborhoods.*

A second important observable dimension of capital prices is the time dimension. Figure 3
Table 2: Price Variation Accounted by Listed Characteristics

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Sale IQR</th>
<th>Sale $R^2$</th>
<th>Rent IQR</th>
<th>Rent $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw Data</td>
<td>0.717</td>
<td>0.000</td>
<td>0.787</td>
<td>0.000</td>
</tr>
<tr>
<td>Location</td>
<td>0.528</td>
<td>0.489</td>
<td>0.488</td>
<td>0.604</td>
</tr>
<tr>
<td>Time</td>
<td>0.717</td>
<td>0.047</td>
<td>0.787</td>
<td>0.116</td>
</tr>
<tr>
<td>Location × Time</td>
<td>0.477</td>
<td>0.548</td>
<td>0.418</td>
<td>0.672</td>
</tr>
<tr>
<td>⋯× Type</td>
<td>0.447</td>
<td>0.581</td>
<td>0.390</td>
<td>0.695</td>
</tr>
<tr>
<td>⋯× Area</td>
<td>0.373</td>
<td>0.682</td>
<td>0.326</td>
<td>0.766</td>
</tr>
<tr>
<td>⋯× Age</td>
<td>0.340</td>
<td>0.733</td>
<td>0.300</td>
<td>0.801</td>
</tr>
<tr>
<td>⋯× Entrance</td>
<td>0.338</td>
<td>0.736</td>
<td>0.299</td>
<td>0.806</td>
</tr>
<tr>
<td>Benchmark</td>
<td>0.332</td>
<td>0.743</td>
<td>0.297</td>
<td>0.810</td>
</tr>
</tbody>
</table>

*Note:* This table shows the $R^2$ and IQR from residuals of different variations in the fixed effects model

$$\log(q_{ijt}) = \alpha_{jt} + Z_i + \varepsilon_{ijt},$$

where $q_{ijt}$ denotes the price of a capital unit $i$ in location $j$ and period $t$, $\alpha_{jt}$ is a location-by-time fixed effect, and $Z_i$ is a vector of fixed effects linked to the characteristics of the capital unit, such as type (office, retail), size, age, and whether it has an entrance at the street level. The row labeled Raw Data presents the statistics for the demeaned raw log prices. The other rows include the mentioned fixed effects in the regression.

shows that, as is well known, the price of capital units experienced large fluctuations over the last 10 years following the contraction from the Great Recession. To quantify the role of time in driving differences in prices, we estimate a model of log prices on time fixed effects: $\log(q_{ijt}) = \alpha_t + \varepsilon_{ijt}$, where $\alpha_t$ is a monthly dummy. Table 2 shows that time fixed effects account for 5%–10% of the variance in posted prices. This result shows that even in the presence of large fluctuations in capital prices, price differences due to aggregate fluctuations are less important to explaining price differences in capital units than their location. Table 2 also presents the results of a fixed-effects model using both the location and time dimensions, $\log(q_{ijt}) = \alpha_{jt} + \varepsilon_{ijt}$. The location-by-time fixed effect, $\alpha_{jt}$, is important to capture price variations due to regional business cycles. As illustrated in Figure 4, regional economic indicators, such as labor-force participation or the unemployment rate, correlate with capital prices in the region. Table 2 shows that location and time account for 55% of the variance in capital prices for sale and 67% of capital prices for rent.
A major conclusion from Table 2 is that between 20% and 25% of the price variance is not explained by characteristics in the listings. Moreover, the IQR of the benchmark specification, where we include all available controls, is around 40% that of the raw data. We conclude this section by stating that a significant price dispersion is listed in the listings. Figure 5 shows the distribution of price residuals, illustrating the relevance of the dispersion in prices not revealed by the characteristics in the listings. We refer to the dispersion of the residuals from the regression of log prices on all fixed effects and controls of the characteristics in the listings as the residual dispersion.
Figure 5: Distribution of Price Residuals

Note: This figure shows the differences in log prices per square feet with respect to its mean for the raw data, pictured in gray, and price residuals after including the fixed effects in Table (2). We winorize the observations that are above the 99.8% and below the 0.2% of the sample. The left panel shows the distributions for sales and the right panel for rentals.

(iii) Price dispersion explained by time-invariant capital characteristics Finally, we explore the role of fixed characteristics of capital units in price variability. For this, we include property fixed effects in the benchmark empirical model, \( \log(q_{ijt}) = \alpha_i + \alpha_{jt} + Z_i + \varepsilon_{ijt} \), where \( \alpha_i \) is a fixed effect at the property level. Table 3 shows the results, which indicate that the model with fixed effects at the unit-of-capital level can account for the bulk of the residual price dispersion, an important fact to discipline such models.

Table 3: Price Variation Accounted by Listed Characteristics in New Entrants

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Sale</th>
<th>Rent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IQR</td>
<td>( R^2 )</td>
</tr>
<tr>
<td>Raw Data</td>
<td>0.666</td>
<td>0.000</td>
</tr>
<tr>
<td>Benchmark</td>
<td>0.284</td>
<td>0.776</td>
</tr>
<tr>
<td>Property Fixed Effect</td>
<td>0.119</td>
<td>0.946</td>
</tr>
</tbody>
</table>

Note: This table extends Table (2) by including a property fixed effect, gathering inference from properties that change their prices while they are active in the dataset. We find that, after including property fixed effects, non-parametrically absorbing all of the property’s time-invariant price determinants, the IQR is roughly 11% and the \( R^2 \) is roughly 0.94.

3.2 Facts 2: Prices, Expected Duration, and Search

Having documented a significant degree of price dispersion in capital units, our remaining facts help inform explanations of why capital units with similar observable characteristics have different prices. We begin by exploring the role of time-to-sell and search frictions, largely studied in labor and product markets, documenting three facts: (i) units with higher residual prices tend to have greater expected durations and less search intensity, (ii) units with higher residual prices tend
to have higher expected revenues, and (iii) residual and predicted prices have relationships with expected duration and search intensity of opposite signs.

(i) Price residuals, expected duration, and search We construct a measure of the expected duration and expected search intensity received at a given price residual by sorting units by their price residual and computing the average duration and search intensity for each percentile in the distribution of price residuals. Panel (a) of Figure 6 shows that there is a positive relationship between residual price and expected duration, meaning that properties with higher residual prices tend to stay in the market longer. Panel (b) of Figure 6 shows a negative relationship between residual price and expected search intensity, meaning that properties with higher residual prices tend to receive less attention in the platform.

**Figure 6: Price Residuals, Expected Duration, and Search Intensity**

![Figure 6](image)

*(A) Price Residual and Expected Duration  (B) Price Residual and Expected Search*

*Note:* This figure shows the relationship between price residuals and expected duration and between residual and expected clicks for the posts for sale in our database. The price residual is obtained after running a regression of log prices on a set of fixed effects and observable characteristics as discussed in the last section. Specifically the figure shows a binned scatter plot of the relationship between price residuals and the variables of interest. We create 100 bins, corresponding to 100 quantiles of the price residual distribution, and then compute averages over the variable of interest across all the posts located in each bin.

To analyze the strength of the relationship between price residual, expected duration, and search, we proceed as in the previous section, and include expected duration and expected search as additional covariates in the fixed-effects models explaining observed prices. It is worth noting that we do not interpret this empirical model as meaning that expected duration and search are exogenous variables driving prices. We, instead, interpret this model as providing evidence of the tightness of the link between the price chosen by the seller and the expected duration and search received by the property. Table 4 shows that, once we include these measures of expected duration and search intensity, we can account for around 95% of the variance in the data. This result is important because it suggests that models that rely on explaining price dispersion through search
frictions can, in principle, explain much of the data. The next two facts expand the possible detailed explanations related to time-to-sell and search frictions.

Table 4: Expected Clicks and Expected Duration

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Sale</th>
<th>Rent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IQR</td>
<td>$R^2$</td>
</tr>
<tr>
<td>Benchmark</td>
<td>0.284</td>
<td>0.776</td>
</tr>
<tr>
<td>Benchmark + E(duration)</td>
<td>0.206</td>
<td>0.891</td>
</tr>
<tr>
<td>Benchmark + E(clicks)</td>
<td>0.092</td>
<td>0.934</td>
</tr>
<tr>
<td>Benchmark + E(dur) + E(clicks)</td>
<td>0.106</td>
<td>0.948</td>
</tr>
</tbody>
</table>

Note: The first row of the Table replicates the last row of Table (2). The following rows add as controls in the regression the expected duration and expected search intensity to check how much dispersion can be explain once we include those variables. The expected duration is the mean duration leaving out the property own duration for properties that have a price residual in the same percentile to that of the property. Expected clicks works in a similar fashion.

(ii) Price residuals and expected revenues The positive relationship between price residual and expected duration suggests a trade-off between price and time-to-sell, giving rise to two standard explanations. One is that sellers are simply indifferent when choosing the price of their posted units: Higher prices are associated with less search from buyers and more time to sell and lower prices are associated with more search and shorter time to sell, but they both provide an equivalent value to the seller. This explanation is akin to that of labor- and product-market models such as (Burdett and Judd, 1983) and (Burdett and Mortensen, 1998). Another related explanation based on this trade-off is price dispersion heterogeneity in sellers’ preferences: More impatient or risk-averse sellers would choose the lower prices associated with a higher selling probability.

We now provide evidence that challenges these two explanations. For this, consider the expected one-period revenue of selling or renting a capital unit based on the expected duration of a given price residual. In particular, for the price residual of unit $i$, compute its selling probability, $p(q_i)$, as the inverse of the expected duration of that unit, described in the previous section. The one-period expected revenue is then simply given by $q_i p(q_i)$. Panel (a) of Figure 7 shows that the expected revenue is increasing in the price residual, meaning that units with higher prices have higher one-period expected revenues, once the lower selling probability associated with the higher price residual is taken into account. Note that the one-period revenue is the payoff that the most impatient seller would receive. If, under the preferences of the most impatient seller, higher price residuals with lower selling probability are preferred, then the higher price residual would also be preferred under any other possible discount factor. Panel (b) shows a similar result using the selling probability from the worst expected duration associated with each price residual. It also shows an increasing relationship, meaning that even if the seller takes into account the worst possible selling probability associated with a price residual, the units with higher price residuals still provide higher...
expected revenue. These results imply that models based on seller’s random strategies and models based on seller’s preference heterogeneity would have difficulty explaining price dispersion, as higher price residuals are associated with greater payoff even under the preference assumptions that most penalize lower selling probabilities.

**Figure 7: Price Residuals and One-Period Expected Revenue**

![Graph](image)

*Note:* The left panel shows the net present value of for-sale units in the case where the discount rate is zero: the NPV for the most impatient seller. We create 100 bins of the price residual distribution and plot the average net present value for the properties in each bin. The right panel shows the net present value if we assume that the draw of duration received by properties in each bin of price residual are two standard deviations below the mean duration for that bin. The right panel shows that even if we give the best chance of obtaining a flat curve between price residuals and net present values, we get an upward relation.

(iii) **Residual vs. predicted price in the relationship with expected duration and search**

The last important fact of this section is that residual prices and predicted prices have relationships with expected duration with opposite signs. By *predicted prices*, we mean the component of a given property linked to its observable characteristics, or the difference between the actual price and the residual. Panel (a) of Figure 10 shows that units with higher price residuals tend to have a higher expected duration. On the other hand, Panel (b) shows that units with higher predicted prices tend to have a lower expected duration.

The different relationships that residual and predicted prices have with expected duration suggest an important role of information. When higher prices stem from listed characteristics, such as the location of the unit, which can be perfectly observed by buyers, higher prices tend to be associated with shorter time to sell. When high prices cannot be easily linked to observable characteristics, then higher prices are associated with longer time to sell. Motivated by this finding, in the next section we develop a model consistent with this fact based on asymmetric information and search frictions. As Guerrieri et al. (2010) have previously shown, in models with both types of frictions, agents can screen principals by accepting lower trading probabilities. In our model, we
Figure 8: Residual and Predicted Prices, and Expected Duration

Note: This figure shows the relationship between price residuals and expected duration and between predicted prices and expected duration for the listings for sale in our database. Price residuals and predicted prices are obtained after running a regression of log prices on a set of fixed effects and observable characteristics as discussed in the last section. Specifically the figure shows a binned scatter plot of each relationship. We create 100 bins, corresponding to 100 quantiles of the price residual/predicted price distribution, and then compute averages over duration across all the listings located in each bin.

interpret the predicted price as an aspect of the quality of capital for which there is perfect information in the market, and the residual price as reflecting information about the quality of capital that the seller possesses but the buyer does not possess. In this framework, observable characteristics are perfectly reflected into prices, and higher “quality” is associated with a higher selling probability. However, when an attribute is only known by the seller, high-quality-capital sellers signal their type by choosing high prices and a low time to sell (a similar role is played by effort in the Spence (1973) model).

We provide supporting evidence of asymmetric information by looking at the slope of the relationship between expected duration and price residuals by the age of the property. That is, we estimate the slope presented in Panel (a) of Figure 10 for 5 subsamples based on the age of the property: (0-2] years, (2,5] years, (5,20] years, (20,30] years, and 30+ years. Figure X shows the results. We can see that in both markets for sale and rent, the slope is increasing with age. This result is consistent with the problem of asymmetric information being more prevalent for older properties, whose prices reflect larger heterogeneity coming from unobservable characteristics. If asymmetric information is more prevalent in the market of older capital units, sellers are more willing to lower trading probabilities as a signaling device of a higher quality.

Before developing this model, we discuss why an alternative explanation, based on sticky prices, would have difficulty explaining the price dispersion observed in the data.
Figure 9: Duration Slope across Property Ages

(A) Residual Prices
(B) Predicted Prices

Note: Figure (a) shows the slope of expected duration on price residuals for properties of different ages. The bars show the 95% confidence intervals. Figure (b) shows the slope of expected duration on predicted prices for properties of different ages. The bars show the 95% confidence intervals. The properties are collapsed at ages (0-2], (2,5], (5,20], (20,30], and 30+.

Figure 10: IQR of Prices across Property Ages

(A) Residual Prices
(B) Predicted Prices

Note: Figure (a) elaborates on Figure (9a), by showing that the dispersion of log price residuals is higher for older properties. The x-axis shows the age of the property in bins (0-5], (5,20], (20,30+] and the y-axis shows the dispersion of price residuals as measured by the interquartile range. Figure (b) elaborates on Figure (10a), by showing that opposed to the behavior of price residuals, the dispersion of expected prices do not follow an increasing pattern with respect to age of the property. The x-axis shows the age of the property in bins (0-5], (5,20], (20,30+] and the y-axis shows the dispersion of price residuals as measured by the interquartile range.
3.3 Facts 3: Sticky Prices

Sticky prices might be simple alternative explanation for price dispersion. If sellers face a cost to change their price, then price dispersion will arise from capital units with different cost of changing prices or posted at different times. To show that this is a plausible explanation in the market for capital, Table 5 shows that only between 4% and 6% of the properties adjust their prices in a given month. The bulk of adjustments are price decreases, which makes intuitive sense since during our sample Spain experienced an economic crisis. When infrequent price changes occur, their size is large. On average, those who reset their prices do it by between 11% and 18%. With price increases being greater than price decreases. The frequency of price changes is lower than that reported for the consumption goods in the U.S. by Nakamura and Steinsson (2008), Bils and Klenow (2004), among others. We find that even when prices are trending down, 20% of the price changes are price increases, a feature that is also shared in the U.S. goods market, where one third of price changes are price decreases even in period with positive inflation Nakamura and Steinsson (2008). Also consistent with the goods literature, and as shown in the appendix, we find no evidence of upward-sloping hazard functions of price changes.

**Table 5: Frequency of Price Changes for Capital**

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Local Rent</th>
<th>Local Sale</th>
<th>Office Rent</th>
<th>Office Sale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency of Price Changes</td>
<td>4.35</td>
<td>4.84</td>
<td>6.05</td>
<td>5.72</td>
</tr>
<tr>
<td>Frequency of Price Increases</td>
<td>0.74</td>
<td>0.82</td>
<td>1.21</td>
<td>0.96</td>
</tr>
<tr>
<td>Frequency of Price Decreases</td>
<td>3.60</td>
<td>4.04</td>
<td>4.84</td>
<td>4.78</td>
</tr>
<tr>
<td>Absolute Size of Price Changes</td>
<td>17.91</td>
<td>13.71</td>
<td>16.85</td>
<td>11.46</td>
</tr>
<tr>
<td>Absolute Size of Price Increases</td>
<td>22.08</td>
<td>16.70</td>
<td>22.44</td>
<td>14.00</td>
</tr>
<tr>
<td>Absolute Size of Price Decreases</td>
<td>16.92</td>
<td>12.98</td>
<td>15.59</td>
<td>10.78</td>
</tr>
</tbody>
</table>

*Note:* The table shows price-adjustment statistics by type of operation (sale and rent). The frequency of price changes is the share of properties that change their price in a given month. Frequency of price increases and decreases denote the share of properties that increased and decreased their price, respectively. Absolute-size statistics denote the absolute value of the percentage change in prices conditional on a price change.

A key test we can conduct with our data to further explore the possibility that price stickiness explaining price dispersion is to analyze the price dispersion of new entrants. If the cost of changing prices is the main explanation of price stickiness, then price dispersion among new entrants, who by definition are incurring the cost of setting a price, should be smaller than for existing listings. Table 6 challenges this idea: The residual dispersion of new entrants is comparable to that of all listings.
Table 6: Price Variation Explained by Listed Characteristics in New Entrants

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Sale IQR</th>
<th>$R^2$</th>
<th>Rent IQR</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw Data</td>
<td>0.666</td>
<td>0.000</td>
<td>0.802</td>
<td>0.000</td>
</tr>
<tr>
<td>Location FE</td>
<td>0.522</td>
<td>0.515</td>
<td>0.459</td>
<td>0.653</td>
</tr>
<tr>
<td>Time FE</td>
<td>0.666</td>
<td>0.092</td>
<td>0.802</td>
<td>0.178</td>
</tr>
<tr>
<td>Location $\times$ Time FE</td>
<td>0.377</td>
<td>0.626</td>
<td>0.224</td>
<td>0.751</td>
</tr>
<tr>
<td>$\cdots \times$ Type FE</td>
<td>0.358</td>
<td>0.650</td>
<td>0.221</td>
<td>0.764</td>
</tr>
<tr>
<td>$\cdots \times$ Area FE</td>
<td>0.308</td>
<td>0.728</td>
<td>0.208</td>
<td>0.814</td>
</tr>
<tr>
<td>$\cdots \times$ Age FE</td>
<td>0.293</td>
<td>0.766</td>
<td>0.203</td>
<td>0.836</td>
</tr>
<tr>
<td>$\cdots \times$ Entrance FE</td>
<td>0.293</td>
<td>0.769</td>
<td>0.203</td>
<td>0.841</td>
</tr>
<tr>
<td>$\cdots +$ Controls (benchmark)</td>
<td>0.284</td>
<td>0.776</td>
<td>0.198</td>
<td>0.845</td>
</tr>
</tbody>
</table>

Note: This table replicates Table (2) only for entrant posts. The idea is that, if price rigidity drives dispersion, then the share of variance explained by only including entrant posts should be significantly greater. That is, observable characteristics should better explain the variation of prices across properties at the time they enter the market.

Therefore, although the fact that capital prices are sticky may be of interest per se for researchers using capital-goods models with pricing frictions, evidence suggests that models of price stickiness would have difficulty explaining price dispersion in the capital market.

4 A Model of Frictional Trading and Price Dispersion in the Physical Capital Market

We construct a tractable model with trade frictions in the physical-capital market that can explain the key empirical facts documented in the previous section. In the model, capital is heterogeneous in its quality and traded in a decentralized market characterized by search frictions. When the quality of capital is public information, units of higher quality trade at higher probabilities, as observed in the data for predicted prices. When there is asymmetric information in the quality of capital, high-quality sellers signal their type by choosing markets with high price and lower trading probabilities, as observed in the data for price residuals.

4.1 Environment

Consider an economy that lasts two periods, $t = 0, 1$, with no aggregate uncertainty.\(^8\)

**Goods and markets** Two goods are traded: final goods and capital goods. Final goods are traded in a Walrasian market. Capital goods are traded in a decentralized market with search frictions.

\(^7\)In particular, these findings can be useful for models that incorporate pricing frictions in investment goods or for multi-sector models with pricing frictions. See, for example, Barsky et al. (2007), Carvalho (2006), and Nakamura and Steinsson (2010).

\(^8\)The extension to infinite horizon is available upon request.
Sellers post capital units in the decentralized market, choosing at what price, \( q \), to post their units. Buyers dedicate labor to search and match, and can direct their search towards a submarket with a specific price. The flow of new matches in submarket (price) \( q \) is given by \( \mathcal{M}(k^s(q), h^s(q)) \), where \( k^s(q) \) and \( h^s(q) \) denote, respectively, capital posted by sellers in submarket \( q \) and hours worked by buyers searching in submarket \( q \). We assume that \( \mathcal{M}(k^s, h^s) = \overline{m}(k^s)^{\eta}(h^s)^{1-\eta} \), where \( \eta \in (0, 1) \) and \( \overline{m} > 0 \). In each submarket \( q \), the market tightness, denoted \( \theta(q) \equiv \frac{h^s(q)}{k^s(q)} \), is defined as the ratio between buyers’ hours of search and the mass of capital posted by sellers. Visiting submarket \( q \) in period \( t \), sellers face a probability \( p(\theta(q)) \equiv \frac{\mathcal{M}(k^s(q), h^s(q))}{k^s(q)} \) of selling capital, and buyers match a mass of capital \( \mu(\theta(q)) \equiv \frac{\mathcal{M}(k^s(q), h^s(q))}{h^s(q)} \) per hour of search.

**Agents, preferences, and technologies** The economy is populated by a unit mass of entrepreneurs and a unit mass of capitalists. Entrepreneurs are endowed with time to work and have preferences described by the lifetime utility \( \sum_{t=0}^{\infty} \beta^t \{ c_t - \chi h_t^2 \} \), where \( c_t \) denotes consumption of the representative entrepreneur in period \( t \), and \( h_t \) hours of work in search activities in period \( t \). Entrepreneurs have access to a technology to produce final goods using capital, given by \( y_t = k_t^{\alpha} \), where \( k_t \) denotes capital used in production, accumulated in the previous period. They have also access to a linear investment technology to accumulate capital out of the final good and a large initial endowment of final goods \( y_0 \).

Capitalists are initially endowed with a stock of capital \( k_0 \). This initial endowment of capital can be of two possible qualities \( \omega \in \Omega \equiv \{ \omega_L, \omega_H \} \), with \( \omega_L < \omega_H \). A mass \( \pi_L \) of capitalists are endowed with low-quality capital, and a mass \( \pi_H = 1 - \pi_L \) with a high-quality capital. This quality, \( \omega \), shifts initial capital into effective units of capital that can be used in production. Capitalists have preferences described by the lifetime utility function \( \sum_{t=0}^{\infty} \beta^t c_{it} \). They have access a technology to produce final goods using capital given by \( \phi k_1 \), with \( \phi < 1 \), where \( k_1 \) denotes their effective capital in period \( t = 1 \). The fact that their technology is relatively less productive introduces gains from trade between capitalists and entrepreneurs.

**Information** In the next subsections, we discuss the equilibrium of the economy under two possible assumptions of information on capital quality: (i) Under full information, a capitalist posts capital to sell in the decentralized market with its quality perfectly observed by all agents.

---

9 The assumed functional form of the matching function is convenient for tractability and is used frequently in related literature on labor search (e.g., Shimer, 2005). It implicitly assumes that \( \overline{m} \) is such that, in equilibrium, the mass of capital matched does not exceed existing capital units (i.e., \( \overline{m}(k^s)^{\eta}(h^s)^{1-\eta} \leq k^s \)).

10 Following the directed search literature (see, for example Moeen, 1997; Menzio and Shi, 2011), in submarkets that are not visited by any sellers, \( \theta(q) \) is an out-of-equilibrium conjecture that helps determine equilibrium. See footnote 13 for more details.

11 In particular, the assumption is that the initial endowment of final goods is large enough to deliver a nonnegative aggregate consumption.
Buyers can direct their search not only towards specific prices, but also to capital goods of specific qualities. (ii) When a capitalist posts capital to sell in the decentralized market under asymmetric information, its quality is private information. Buyers can still direct their search towards specific prices, but cannot distinguish capital units of different qualities at a given price.

4.2 Full Information

**Optimization**  Under full information, the problem of the representative entrepreneur is given by

$$\max_{k_1, i, h_j^s(q) \geq 0} \quad c_0 + \beta c_1 - \chi \sum_{j \in \{L, H\}} \int_{q \in \mathbb{R}_+} h_j^s(q) \, dq$$

$$\text{s.t.} \quad c_0 + i + \sum_{j \in \{L, H\}} \int_{q \in \mathbb{R}_+} q \mu(\theta_j(q)) \, h_j^s(q) \, dq = y_0,$$

$$c_1 = k_1^0,$$

$$k_1 = i + \sum_{j \in \{L, H\}} \omega_j \int_{q \in \mathbb{R}_+} \mu(\theta_j(q)) \, h_j^s(q) \, dq,$$

where $h_j^s(q)$ denotes the hours worked searching for capital of quality $j \in \{L, H\}$ in submarket $q$, $i$ denotes the production of new capital goods. In these expressions, we drop time subscripts in investment and search variables, which only occur in the period 0. Equations (1) and (2) are the entrepreneur’s budget constraints. The former incorporates the cost of the two forms of investment, namely, the production of new capital goods, $i$, and the capital purchases in the decentralized market, $q \mu(\theta_j(q)) \, h_j^s(q)$. Equation (3) is the capital accumulation constraint for entrepreneurs, taking into account the quality of capital units purchased in the decentralized market, meaning that if entrepreneurs match a mass of capital $\mu(\theta_j(q)) \, h_j^s(q)$, their effective capital is given by $\omega_j \mu(\theta_j(q)) \, h_j^s(q)$. In the formulation of problem (P1), we have assumed that investment $i$ can be negative, so entrepreneurs can transform matched capital into final goods. We have also assumed that entrepreneurs do not face any financial constraint on their investment activities. Together, these assumption imply that entrepreneurs play the role of arbitrageurs in the market for capital, ensuring that in every submarket the cost of purchasing capital cannot be more than the cost of producing it. Formally, the key optimality condition from the entrepreneurs’ problem is their indifference between purchasing capital in the decentralized market and investing in new capital in all submarkets $q_j$ visited by a positive mass of capitalists:

$$h_j^s(q)(\mu(\theta_j(q))(q - \omega_j) + \chi)^+ = 0,$$
which means that in open submarkets in which entrepreneurs are willing to search, the cost per unit of capital in that submarket \( \frac{1}{\omega_j} \left( q + \frac{\chi}{\mu(\theta_j(q))} \right) \) is equal to the unit cost of producing it.\(^{12}\) See the appendix for a derivation of this condition. For submarkets visited by a positive mass of capitalists, condition (4) determines the equilibrium market tightness function \( \theta_j(q) \). Following the directed search literature, we also assume that (4) also determines the market tightness function in submarkets not visited by capitalists in equilibrium.\(^{13}\) This assumption implies that the equilibrium market-tightness function faced by capitalists is given by

\[
\theta_j(q_j) = \mu_j^{-1} \left( \frac{\chi}{\omega_j - q_j} \right),
\]

for all \( q < \omega_j \), and \( \theta_j(q) = 0 \) for all \( q \geq \omega_j \), meaning that capital units listed above the entrepreneurs’ value of capital remain unmatched.

The problem of a capitalist of type \( j \in \{L, H\} \) is given by

\[
\max_{s_j, q_j} \ c_{j0} + \beta c_{j1}
\]

subject to

\[
\begin{align*}
\ c_{j0} & = s_j p(\theta_j(q_j))q_j \pi_j k_0, \\
\ c_{j1} & = (s_j (1 - p(\theta_j(q_j))) + (1 - s_j)) \phi \pi_j \omega_j k_0,
\end{align*}
\]

given \( k_0 \), where \( s_j \in \{0, 1\} \) is an indicator variable that takes the value of one if the capitalist decides to participate in the decentralized market selling capital.\(^{14}\) Equation (7) is the capitalist’s period-0 budget constraint, linking consumption to the revenues from selling capital given the choice of prices. Equation (8) is capitalist’s period-1 budget constraint linking consumption to the revenue from producing with unsold capital units. An interior solution to this problem can be characterized by the first-order condition

\[
p(\theta_j(q_j)) = -(q_j - \phi \beta \omega_j) p'(\theta_j(q_j)) \theta'_j(q_j),
\]

which equates the marginal benefit of increasing the price of posted capital \( p(\theta_j(q_j)) \) to the marginal cost in terms of decrease in selling probability \( p'(\theta_j(q_j)) \theta'_j(q_j) \) valued at the net revenue made on each unit \( (q_j - \phi \beta \omega_j) \). (The proof in Appendix 1 shows that this condition characterizes

\footnote{We restrict attention to interior solutions of the entrepreneur’s problem given that, in equilibrium, if there exist a \( q \) for which \( h'_j(q) > 0 \) and \( \mu(\theta_j(q))q + \chi < \mu(\theta_j(q)) \omega_j \), then \( h'_j(q) \to \infty \) and for any initial finite \( k_0 \) it will be that \( \mu(\theta_j(q)) \to 0 \), contradicting that \( \mu(\theta_j(q))q + \chi < \mu(\theta_j(q)) \omega_j \).}

\footnote{As argued in Menzio and Shi (2011) a justification of this assumption come from considering a sequential game in which capitalists choose with a tremble their posted prices and then entrepreneurs choose in what submarkets to search. Because of the tremble, the tightness is well defined for all \( q \). As we make the tremble arbitrarily small \( \theta_j(q) \) converges to (5).}

\footnote{Allowing capitalist to search in multiple submarkets would lead to the same equilibrium.}
the capitalists’ optimal choice under the equilibrium market-tightness function).

**Equilibrium** A competitive equilibrium in the economy under full information can be defined as follows.

**Definition 1 (Equilibrium under full information).** An equilibrium under full information is a set of allocations \((q_j)_{j \in \{L,H\}}\) and market-tightness functions, \((\theta_j(q) : \mathbb{R}_+ \to \mathbb{R}_+)_{j \in \{L,H\}}\), such that

i. Market tightness functions satisfy (5).

ii. Allocations solve the capitalists’ problem at the equilibrium market-tightness functions.

The following result derives the equilibrium price of capital and market tightness for each type of capital under full information. All proofs are in the appendix.

**Proposition 1.** Under full information, there exists a unique equilibrium in which the price of capital and market tightness for capital quality \(j\) are given by

\[ q_{FI}^j = \omega_j \eta (1 - \eta) \phi \beta \]

and

\[ \theta_{FI}^j (q_{FI}^j) = \theta_j (q_{FI}^j) = (\omega_j m \chi^{-1} (1 - \eta) (1 - \phi \beta))^{\frac{1}{\eta}}. \]

This result is graphically represented in Figure 11. Dashed lines represent the isocost curves of entrepreneurs, the one corresponding to the high quality \(\omega_H\) being simply shifted upward by the difference in quality with \(\omega_L\). Solid lines denote the isorevenue curve of capitalists, the one of the capitalist with high-quality capital having a lower slope. This is the result of requiring a lower “compensation” in terms of higher probability of sale for a given reduction of prices, since the outside option is increasing in the quality of capital. Proposition 1 shows that under full information the price of a unit of capital and its matching rate are increasing in the quality of capital, which implies the following result.

**Corollary 1.** In an equilibrium under full information, capital units with higher prices have higher matching rates. That is, \(q_{FI}^H > q_{FI}^L\) and \(p(\theta_{FI}^H) > p(\theta_{FI}^L)\).

If the assumption of full information in the model is interpreted in the data as capturing characteristics of capital that are posted in the listing, this result implies that search frictions can account for the negative relationship observed in the data between predicted prices and time-to-sell of capital units. To see the intuition behind this result, replace the equilibrium price of capital in the equilibrium market tightness function (5) to obtain

\[ \omega_j (1 - \eta) (1 - \phi \beta) = \frac{\chi}{\mu(\theta_j (q_j))}. \]

22
Equation (10) means that, in equilibrium, the net benefit for entrepreneurs from purchasing a unit of capital in the decentralized market relative to producing it has to be equal to its search cost. As the price of capital scales with its quality, so do its net gains. By non-arbitrage, the search cost must be higher on capital units with higher productivity, meaning that sellers of these units match at a higher rate.

4.3 Asymmetric Information

Setup We now analyze a setup under which only the capitalist knows the quality of her capital. The timing of the game is as follows.

i. Nature chooses the quality of capital units for each capitalist.

ii. Capitalists post a price for their capital units $q$, which is perfectly observed by all agents.

iii. Entrepreneurs choose their search effort for capital units at different prices.

This setup requires specifying the entrepreneur’s beliefs about the type of capital given a price posted. We assume all entrepreneurs have the same beliefs. We describe beliefs by the mapping $\lambda_L(q) : \mathbb{R}_+ \to [0, 1]$, which denotes the probability of that a unit of capital is of type $\omega_L$ given the
price of capital $q$, and denote by $\omega^e(q) \equiv \omega_L \lambda_L(q) + \omega_H (1 - \lambda_L(q))$ the expected quality at the price, $q$, under beliefs $\lambda_L$.

**Optimization** Under this signaling game, the entrepreneurs’ indifference condition implies an equilibrium market tightness function given by

$$\theta(q) = \mu^{-1}\left(\frac{\chi}{\omega^e(q) - q}\right), \quad (11)$$

for all $q < \omega^e(q)$, and $\theta(q) = 0$ for all $q \geq \omega^e(q)$.

The problem of a capitalist of type $j \in \{L, H\}$, in turn, is given by

$$
\max_{s_j, q_j} c_{j0} + \beta c_{j1}
$$

s.t. $c_{j0} = s_j p(\theta(q_j)) q_j \pi_j k_0$,

$$
c_{j1} = (s_j (1 - p(\theta(q_j))) + (1 - s_j)) \phi \pi_j \omega_j k_0,
$$

where $q_j$ denotes the submarket choice of a capitalist of type $j$. Although the structure of this problem is similar to that under full information, capitalists in this setup must take into account that their choice of prices can signal their capital quality, which will be reflected in the equilibrium-tightness function $\theta(q_j)$.

**Equilibrium** An equilibrium in the economy under asymmetric information is defined as follows.

**Definition 2.** A Perfect Bayesian Equilibrium in the economy with asymmetric information is a set of allocations $\{(q_j)_{j \in \{L, H\}}\}$, a market tightness function, $\theta(q) : \mathbb{R}_+ \to \mathbb{R}_+$, and beliefs $\lambda_L(q) : \mathbb{R}_+ \to [0, 1]$, such that:

i. Market tightness function satisfies the entrepreneurs’ indifference (11).

ii. Allocations solve the capitalists’ problem at the equilibrium market-tightness functions and beliefs.

iii. The belief function is derived from capitalists’ strategies using Bayes’ rule where possible.

An important property of an equilibrium under asymmetric information is the single-crossing condition:

**Lemma 1.** Equilibria under asymmetric information feature $\theta(q_H^{AI}) \leq \theta(q_L^{AI})$.
This result is driven by the fact that the low type has a higher marginal cost of not trading. A high type can never choose a lower probability of not trading than the low type because, if the low type weakly prefers a low trading probability to a high trading probability, the high type would strictly prefer it. This property is important because it means that the model has the potential to provide a rationale for the fact observed in the data that units with a high price residual have a lower trading probability. If the price residual in the data reflects quality that is only observed by the seller, then, unlike in the full-information model, high-quality sellers in this model would never choose a higher trading probability than low-quality sellers. Still, to explain the price dispersion observed in the data, it must be that different types choose different allocations. We study this possibility next.

In the setup considered, there are many equilibria, each of them supported by appropriate out-of-equilibrium beliefs. Of particular interest to studying price dispersion are separating equilibria, which satisfy the following additional condition.

**Definition 3.** A separating equilibrium under asymmetric information is an equilibrium in which the different types post different prices $q_{AI}^L$ and $q_{AI}^H$.

An implication of this definition is that prices reveal the quality of each unit of capital. In a separating equilibrium, two conditions must be satisfied. Denoting by $\theta_{AI}^L = \theta(q_{AI}^L)$ and $\theta_{AI}^H = \theta(q_{AI}^H)$ the allocation under a separating equilibrium, it must be that the low type does not want to mimic the high type,

$$p(\theta_{AI}^L)q_{AI}^L + (1 - p(\theta_{AI}^L)) \phi \beta \omega_L \geq p(\theta_{AI}^H)q_{AI}^H + (1 - p(\theta_{AI}^H)) \phi \beta \omega_L,$$

and that the high type does not want to mimic the low type,

$$p(\theta_{AI}^H)q_{AI}^H + (1 - p(\theta_{AI}^H)) \phi \beta \omega_H \geq p(\theta_{AI}^L)q_{AI}^L + (1 - p(\theta_{AI}^L)) \phi \beta \omega_H.$$

We consider equilibria in which the low type chooses the best market for himself, knowing that buyers will offer a price consistent with the low quality of the capital unit.\(^{15}\) The solution to the low-type capitalists’ problem is the same as in the case with full information and characterized by equation (9). The following result provides sufficient conditions for the existence of a separating equilibrium.

\(^{15}\)The reason for this is that there cannot be a separating equilibrium in which the high type chooses the best market for himself, knowing that buyers will offer a price consistent with the high quality of the capital unit. If this were the case, the high type’s optimal choice of submarket is given by equation (9) evaluated at $\omega_H$. Such a solution involves a high price and a high trading probability, compared to the best the low type could obtain in the submarket for low-quality capital. But then the low type would have strong incentives to mimic the high type, so such separating equilibrium cannot exist.
**Proposition 2.** If $\phi \beta \omega_H > \omega_L$, a separating equilibrium always exist.

The previous proposition shows that a separating equilibrium exists, although in fact a continuum of separating equilibria exist that satisfy conditions (12) and (13). The reason for this is that the definition of a separating equilibrium does not impose any constraints on off-equilibrium beliefs. The following result imposes more structure on these beliefs by considering the equilibrium that satisfies the *intuitive criterion* (IC) of Cho and Kreps (1987).

**Proposition 3.** If $\phi \beta \omega_H > \omega_L$ there exists a unique equilibrium that satisfies the IC. This is a separating equilibrium, in which the allocation, $\{\theta^A_L, \theta^A_H\}$, and prices, $\{q^A_L, q^A_H\}$, are such that

$$\theta^A_L = \arg\max_{q^A_L} p(\theta^A_L(q^A_L))q^A_L + (1 - p(\theta^A_L(q^A_L))) \phi \beta \omega_L$$

$$p(\theta^A_L(q^A_L))q^A_L + (1 - p(\theta^A_L)) \phi \beta \omega_L = p(\theta^A_H(q^A_H) + (1 - p(\theta^A_H)) \phi \beta \omega_L$$

and $q^A_j = \omega_j - \frac{\chi}{\mu(\theta^A_j)}$.

The intuition behind this result can be seen in Figure 12. In a separating equilibrium, the outcome in the submarket for the low quality capital is the same as the one obtained under full information (see Figure 11). However, the outcome in the submarket for high quality capital is dis-
torted by the fact that high-quality capitalists maximize expected utility subject to the constraint that low-quality capitalists do not have a strict preference for participating in their submarket and given entrepreneurs’ belief function. Although there are multiple separating equilibria supported by different sets of beliefs (see the proof of Proposition 3 in the Appendix), the unique separating equilibrium that satisfies the intuitive criterion is the one depicted in Figure 12. In such an equilibrium, the high-quality capitalist chooses the allocation that makes the low-quality capitalist just indifferent between mimicking and not, because it minimizes the signaling “effort” imposed by the low trading probability. Thus, the following simple result follows from the separating equilibrium with important implications for explaining the patterns observed in the data.

**Corollary 2.** In the unique separating equilibrium with asymmetric information that satisfies the IC, capital units with higher prices have lower matching rates: \( q_{AI}^H > q_{AI}^L \) and \( p(\theta_{AI}^H) < p(\theta_{AI}^L) \).

This result is important because it shows that the combination of search frictions and asymmetric information can explain why, in the data, higher price residuals are associated with lower trading probabilities. The model predicts that owners of capital units that possess characteristics that are not possible to announce in a posting signal their type by choosing a high price, associated with low trading probabilities, which is not easy to mimic by the owners of low-quality capital with their high marginal cost of not trading. For this reason, while the market tightness faced by the low type is the same under full and asymmetric information \( (\theta_{AI}^L = \theta_{FI}^L) \), tightness faced by the high type is lower under asymmetric information than under full information \( (\theta_{AI}^H < \theta_{FI}^H) \). Give that, under full information, high types face high market tightness, this implies an important qualitative change created by asymmetric information and signaling.

### 4.4 Efficiency

In the presence of signaling, the separating equilibrium can be Pareto dominated by equilibrium when signaling is not possible. This is illustrated with the following result:

**Proposition 4.** There exists a \( \pi_L \) such that if \( \pi_L \leq \pi_L \), a pooling allocation allocation with \( q^P = \bar{\omega}(\eta+(1-\eta)\phi\beta) \) and \( \theta^P = (\bar{\omega}m\chi^{-1}(1-\eta)(1-\phi\beta))^{\frac{1}{3}} \) with \( \bar{\omega} = \pi_L\omega_L+(1-\pi_L)\omega_H \), Pareto dominates the allocation under the separating equilibrium of Proposition 3.

It is simple to show that the planner can implement the pooling allocation with a tax schedule \( \tau(q) \) on buyers (taxing capital units sold at higher prices) or by implementing controls on prices (similar to “rent controls” observed in practice).
5 Quantifying Frictions and Policies: Model and Data

In this section, we calibrate the model to quantify the extent of the inefficiency created by asymmetric information in the market for physical capital, and to study whether the Pareto improvement given by a pooling equilibrium is available or not. We choose to calibrate the model to a monthly frequency. Table 7 displays the values of calibrated parameters. A first group of parameters is set outside of our calibration exercise: $\beta$, $\eta$, $\omega_L$, $k_H$ and $k_L$. The subjective discount factor $\beta$ is chosen to match an annualized rate of 4%. The elasticity of the matching function $\eta$ is set to 0.86, following Ottonello (2017). Without loss of generality, we normalize the productivity of the low-quality capital to one. Finally, since in our calibration exercise we target the IQR of residual prices, we set $k_L = k_H = 0.5$ (the second inequality is a normalization). We jointly calibrate a second group of parameters: $\omega_H$, $\chi$, $\phi$ and $\bar{m}$. For this, we choose 4 moments as targets of the calibration of the model under asymmetric information: the IQR of (log) residual prices, the corresponding predicted probabilities of a sale obtained from Figure 8a,\(^{16}\) and an average transaction cost of 3% of the average transacted price.\(^{17}\) Although there is no one-to-one mapping from parameters to moments, we provide intuition of the identification of the model parameters. We find that the average transaction cost is pinned down by the cost of search per unit of search effort $\chi$ and that the average transaction probability is pinned down by the matching efficiency $\bar{m}$.

<table>
<thead>
<tr>
<th>Table 7: Calibrated Parameters</th>
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<tbody>
<tr>
<td>Parameter</td>
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<tr>
<td>Predetermined</td>
</tr>
<tr>
<td>$\beta$</td>
</tr>
<tr>
<td>$\eta$</td>
</tr>
<tr>
<td>$\omega_L$</td>
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<tr>
<td>$k_L, k_H$</td>
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<tr>
<td>Calibrated</td>
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<tr>
<td>$\omega_H$</td>
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<tr>
<td>$\chi$</td>
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<tr>
<td>$\phi$</td>
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<tr>
<td>$\bar{m}$</td>
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</tbody>
</table>

Table 8 shows the goodness of fit of the calibration of the model under asymmetric information. Overall, the model is able to reproduce the targeted moments fairly well. In addition, the model is able to reproduce additional untargeted moments. In the last two columns of the table, we show the ability of the model to match moments associated with the observable characteristics of physical

\(^{16}\)The underlying assumption is that expected duration follows a geometric distribution, so that the per-period probability of a sale for a capital unit with price $p$ can be retrieved as $1/\text{Duration}(p)$.

\(^{17}\)Formally, the corresponding target in our model is given by $\sum_{j=\{L,H\}} \frac{k_j p(\theta_j^{AI})}{k_L p(\theta_L^{AI}) + k_H p(\theta_H^{AI})} \left( \frac{(\chi/\mu(\theta_j^{AI}))}{(\chi/\mu(\theta_j^{AI})) + q_j} \right)$.
capital: the IQR of (log) predicted prices and the corresponding predicted probabilities of a sale obtained from Figure 8b. Under full information, the ratio of prices is equal to the ratio of qualities, $q_H/q_L = \omega_H/\omega_L$. Therefore, given the normalization $\omega_L = 1$, we can calibrate $\omega_H$ to perfectly match the IQR of predicted prices and compare the model predictions for the sale probabilities $p(\theta_{FI}^L)$ and $p(\theta_{FI}^H)$ using the parameters calibrated under asymmetric information. We see that the model is able to reproduce well the average probability of a sale and the slope of these probabilities across submarkets.

Table 8: Goodness of Fit

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<tr>
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</thead>
<tbody>
<tr>
<td>$\log(q_H) - \log(q_L)$</td>
<td>0.426</td>
<td>0.330</td>
<td>0.940</td>
<td>0.940</td>
</tr>
<tr>
<td>$p(\theta_{FI}^L)$</td>
<td>0.083</td>
<td>0.099</td>
<td>0.081</td>
<td>0.099</td>
</tr>
<tr>
<td>$p(\theta_{FI}^H)$</td>
<td>0.067</td>
<td>0.044</td>
<td>0.086</td>
<td>0.115</td>
</tr>
<tr>
<td>Avg. search cost</td>
<td>0.030</td>
<td>0.034</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Finally, we use the calibrated model to quantify the efficiency loss generated by asymmetric information and explore whether the allocation under asymmetric information is Pareto inefficient. Table 9 reports the analysis of these counterfactual scenarios. First, we can quantify the relevance of asymmetric information by comparing the equilibrium under asymmetric information with the counterfactual equilibrium under. Although the low-quality capitalist is not affected by asymmetric information, the high-quality capitalist experience a drop if expected consumption of 2.3%. This is the result of having to raise the price and experience a lower trading probability (from 10.3% to 4.4%) in order to signal the higher quality of her capital. The losses generated by asymmetric information can be also quantified by comparing the amount of efficiency units of capital that are traded in both equilibria, which decreases from 0.118 to 0.079 (a loss of 6.7%).

As shown in Proposition 4, the separating equilibrium could be inefficient if the share of low-quality capitalists is small enough. We analyze whether this is the case in our calibration, and verify that it is indeed the case that the separating equilibrium is inefficient. Therefore, a pooling equilibrium with taxes that make setting prices above $(\pi_L \omega_L + (1 - \pi_L) \omega_H)(\eta + (1 - \eta) \phi \beta)$ costly enough (e.g., price controls) Pareto dominates the separating equilibrium. The gain experienced by the low-quality capitalist corresponds to an increase in expected consumption of 2.4%, while the gain experienced by the high-quality capitalist is equal to 0.5%.18

18The amount of matched efficiency units of capital under full information and the pooling equilibrium (social planner’s allocation) are not equal, although they are similar in magnitude given the small differences in trading probabilities for both types of capitalists.
6 Conclusion

In this paper, we document the relevance of price dispersion in the physical-capital market. Using data on nonresidential structures posted in the market to be traded, we show that a fourth of their price differences cannot be linked to their observable characteristics. We provide empirical evidence and a model of frictional trading in the physical capital market that explains price dispersion with the interaction between asymmetric information and search frictions. Mapping our model to the data, we quantify a large degree of asymmetric information and discuss policies aimed at improving market efficiency.
References


Appendix

**Derivation of condition (4).** Denoting by $Q$ the Lagrange multiplier associated with condition (3) and by $\Xi q_j$ the Lagrange multiplier associated to $h^s(q_j) \geq 0$, an interior solution of problem (P1) is characterized by the first-order conditions

$(i :)$ $Q = 1,$ \hspace{1cm} (14)

$(k_1 :)$ $Q = \beta \alpha k_1^{\alpha - 1},$ \hspace{1cm} (15)

$(h^s(q_j) :)$ $\mu_j(\theta_j(q_j))q_j + \chi = Q\mu_j(\theta_j(q_j))\omega_j + \Xi q_j,$ \hspace{1cm} (16)

and the complementary slackness condition

$$\Xi q_j h^s(q_j) = 0.$$ \hspace{1cm} (17)

Combining (14), (16), and (17), obtain (4). As mentioned in the text, we restrict attention to interior solutions given that, in equilibrium, if there exist a $q_j$ for which $h^s(q_j) > 0$ and $\mu_j(\theta_j(q_j))q_j + \chi < \mu_j(\theta_j(q_j))\omega_j$, then $h^s(q_j) \to \infty$ and for any initial finite $k_0$ it will be that $\mu_j(\theta_j(q_j)) \to 0$, contradicting that $\mu_j(\theta_j(q_j))q_j + \chi < \mu_j(\theta_j(q_j))\omega_j$.

**Proof of Proposition 1.** Using the Cobb-Douglas matching function, the equilibrium market-tightness function faced by capitalists is given by

$$\theta_j(q_j) = \left(\frac{m(\omega_j - q_j)}{\chi}\right)^{\frac{1}{\eta}},$$ \hspace{1cm} (18)

for all $q_j < \omega_j$, and $\theta_j(q_j) = 0$ for all $q_j \geq \omega_j$.

Given the equilibrium market tightness function (18), capitalists always pick to participate in the decentralized market ($s_j = 1$) because, for any $q_j \in (\phi \beta \omega_j, \omega_j)$, $(q_j - \phi \beta \omega_j)p(\theta(q_j)) > 0$. To determine the optimal choice of submarket express the capitalist’s problem with $s_j = 1$ as

$$\max_{q_j} p(\theta_j(q_j))q_j + \beta(1 - p(\theta_j(q_j)))\phi \omega_j$$ \hspace{1cm} (19)

By the same argument as before for the participation choice, we know that, given the equilibrium market tightness function (18), the solution to this problem implies $q_j \in (\phi \beta \omega_j, \omega_j)$. In this interval, capitalist’s objective function is strictly concave, and the optimal choice of submarket is determined
by the first-order condition (9), which using the Cobb-Douglas matching function is given by:

\[ q_j = \omega_j(\eta + (1 - \eta)\phi \beta). \tag{20} \]

Replacing (20) in (18), obtain the equilibrium market tightness of capital quality \( j \),

\[ \theta_j \equiv \theta_j(q_j) = \left( \frac{\omega_j m (1 - \eta)(1 - \phi \beta)}{\chi} \right)^{\frac{1}{\beta}}. \]

**Proof of Lemma 1.** Capitalists of type \( H \) could have chosen \( \theta(q_L) \) rather than \( \theta(q_H) \), which means that

\[
p(\theta(q_H))q_H + (1 - p(\theta(q_H)))\phi \beta \omega_H \geq p(\theta(q_L))q_L + (1 - p(\theta(q_L)))\phi \beta \omega_H
\]

\[
p(\theta(q_H))(\omega^e(q_H) - \phi \beta \omega_H) - \theta(q_H)\chi \geq p(\theta(q_L))(\omega^e(q_L) - \phi \beta \omega_L) - \theta(q_L)\chi, \tag{21}
\]

where the second inequality follows from replacing \( q_H + \frac{\chi}{\mu(\theta(q_H))} = \omega^e(q_H) \). Similarly, capitalists of type \( L \) could have chosen \( \theta_L \) rather than \( \theta_L \) which means that

\[
p(\theta(q_L))(\omega^e(q_L) - \phi \beta \omega_L) - \theta(q_L)\chi \geq p(\theta(q_H))(\omega^e(q_H) - \phi \beta \omega_L) - \theta(q_H)\chi. \tag{22}
\]

Combining (21) and (22), we obtain the following inequality

\[
p(\theta(q_H))(\omega^e(q_H) - \phi \beta \omega_H) - \theta(q_H)\chi + p(\theta(q_L))(\omega^e(q_L) - \phi \beta \omega_L) - \theta(q_L)\chi
\]

\[ \geq p(\theta(q_L))(\omega^e(q_L) - \phi \beta \omega_H) - \theta(q_L)\chi + p(\theta(q_H))(\omega^e(q_H) - \phi \beta \omega_L) - \theta(q_H)\chi,
\]

which can be simplified to

\[
(p(\theta(q_L)) - p(\theta(q_H)))(\omega_H - \omega_L) \geq 0
\]

Given that \( \omega_H > \omega_L \), it follows that \( p(\theta(q_L)) \geq p(\theta(q_H)) \).

**Proof of Proposition 2.** After replacing prices from equation (11) into equations (12) and (13), the following inequalities must hold for a given \( \theta_L \):

\[
p(\theta_L)(1 - \phi \beta)\omega_L - \theta_L\chi \geq p(\theta_H)(\omega_H - \phi \beta \omega_L) - \theta_H\chi \tag{23}
\]
and
\[ p(\theta_H)(1 - \phi \beta)\omega_H - \theta_H \chi \geq p(\theta_L)(\omega_L - \phi \beta \omega_H) - \theta_L \chi. \]  

(24)

First, notice that for the low type to be willing to participate, it has to be that the left-hand-side of (23) is non-negative. Given that \( \lim_{\theta_H \to 0} p(\theta_H)(\omega_H - \phi \beta \omega_L) - \theta_H \chi = 0 \), one can always find a \( \theta_H \) sufficiently low such that this condition is satisfied. In the second place, rewrite equation (24) as:

\[ p(\theta_H)(1 - \phi \beta)\omega_H \geq p(\theta_L)(\omega_L - \phi \beta \omega_H) - (\theta_L - \theta_H)\chi. \]

Therefore, a sufficient condition for this condition to be satisfied is \( \phi \beta \omega_H > \omega_L \).

\[ \blacksquare \]

**Proof of Proposition 3.** In order to prove this result, we first describe the properties of the expected revenues for each type of capitalist keeping beliefs constant. For some given fixed beliefs \( \bar{\omega}_e \), the expected revenue of capitalist \( j \) is given by

\[ p(\theta_j) \left( \bar{\omega}_e - \frac{\chi}{\mu(\theta_j)} \right) + (1 - p(\theta_j)) \phi \beta \omega_j. \]

The first derivative is given by

\[ p'(\theta_j) (\bar{\omega}_e - \phi \beta \omega_j) - \chi \]

and the second derivative is given by

\[ p''(\theta_j) (\bar{\omega}_e - \phi \beta \omega_j). \]

Given that the matching function is Cobb-Douglas, as long as \( \bar{\omega}_e > \phi \beta \omega_j \), expected revenues are strictly concave in \( \theta_j \) and the optimum tightness \( \theta^*_j \) is obtained by equating equation (6) to zero. A result that will become useful later in the proof is the fact that any \( \theta_j < \theta^*_j \) implies that \( p'(\theta_j) (\bar{\omega}_e - \phi \beta \omega_j) - \chi > 0 \), so \( \theta_j \) lies on the increasing part of the expected revenue function.

The first step consists of ruling out equilibria in which both types choose the same market with tightness \( \hat{\theta} \) with some positive probability. In this submarket, buyers are willing to pay a price \( \hat{q} \), which is given by

\[ \hat{q} = (1 - \hat{\lambda})\omega_H + \hat{\lambda} \omega_L - \frac{\chi}{\mu(\hat{\theta})}, \]

where \( \hat{\lambda} \equiv \lambda_L(\hat{q}) \) represents the buyers’ posterior belief. On equilibrium, the payoff of the low type
of choosing such a market is given by

\[ p(\hat{\theta}) \left( (1 - \hat{\lambda})\omega_H + \hat{\lambda}\omega_L - \frac{X}{\mu(\hat{\theta})} \right) + (1 - p(\hat{\theta})) \phi_2\omega_L. \]

We want to show that there exists a ̂ \( \tilde{\theta} < \hat{\theta} \) such that

\[ p(\hat{\theta}) \left( (1 - \hat{\lambda})\omega_H + \hat{\lambda}\omega_L - \frac{X}{\mu(\hat{\theta})} - \phi_2\omega_L \right) + \phi_2\omega_L = p(\tilde{\theta}) \left( \omega_H - \frac{X}{\mu(\tilde{\theta})} - \phi_2\omega_L \right) + \phi_2\omega_L, \tag{25} \]

and at the same time

\[ p(\tilde{\theta}) \left( (1 - \hat{\lambda})\omega_H + \hat{\lambda}\omega_L - \frac{X}{\mu(\tilde{\theta})} - \phi_2\omega_H \right) + \phi_2\omega_H < p(\hat{\theta}) \left( \omega_H - \frac{X}{\mu(\hat{\theta})} - \phi_2\omega_H \right) + \phi_2\omega_H. \tag{26} \]

To show this, solve for ̂ \( \tilde{\theta} \) from equation (25)

\[ p(\hat{\theta}) = p(\tilde{\theta}) \frac{(1 - \hat{\lambda})\omega_H + \hat{\lambda}\omega_L - \frac{X}{\mu(\hat{\theta})} - \phi_2\omega_L}{(\omega_H - \frac{X}{\mu(\tilde{\theta})} - \phi_2\omega_L)}. \]

and replace in equation (26). Then, the inequality can be simplified to

\[ 0 < \hat{\lambda}\phi_2(\omega_H - \omega_L)^2 + \frac{\phi_2\chi}{\mu(\hat{\theta})\mu(\hat{\theta})} (\omega_H - \omega_L) \left( (\mu(\hat{\theta}) - \mu(\hat{\theta})) \right). \]

Note that the first term is always positive. For the second term, since ̂ \( \tilde{\theta} < \hat{\theta} \), then ̂ \( \tilde{\theta} \rightarrow \mu(\hat{\theta}) \) and the last term is strictly positive. Then, choose ̂ \( \tilde{\theta} = \hat{\theta} - \epsilon \) (for a small \( \epsilon > 0 \)) such that the low type is strictly worse off and the high type is strictly better off relative to the pooling allocation.\(^\text{19}\)

Moreover, by IC if the buyer observes this strategy she must believe that it is coming from the high type with probability one. Then, the high type benefits from this deviation and will play ̂ \( \tilde{\theta} \) instead of \( \hat{\theta} \).

Next, consider all separating equilibria. First, notice that in a fully revealing equilibrium, the

\(^{19}\)Equation (25) admits two solutions for \( \tilde{\theta}, \hat{\theta}_1, \) and \( \hat{\theta}_2 > \hat{\theta}_1 \). However, a profitable deviation such as the one described above can be constructed by choosing the lowest \( \hat{\theta} \) that satisfies equation (25). Then, the fact that such \( \epsilon > 0 \) exists follows from the following argument. Define the revenue function \( R_{L,H}(\theta) \equiv p(\theta)(\omega_H - \phi_2\omega_L) - \theta \chi + \phi_2\omega_L \). It can be seen that \( R_{L,H}(\tilde{\theta}) > p(\tilde{\theta}) ((1 - \lambda)\omega_H + \hat{\lambda}\omega_L - \phi_2\omega_L) - \chi \tilde{\theta} + \phi_2\omega_L \geq R_{L,H}(0) \). The expression in the middle of the inequality constraints is equal to the left-hand side of equation (25). The first inequality follows from the fact that in a pooling equilibrium \( 0 < \lambda < 1 \). The second inequality follows from the fact that capitalists are choosing such a submarket, which means that they must be better off than choosing not to sell any capital unit and get a utility of \( \phi_2\omega_L \). Then, the strict concavity of \( R_{L,H}(\theta) \) implies that \( \hat{\theta}_1 < \tilde{\theta} < \hat{\theta}_2 \). By continuity of the matching function, it must be that the solution \( \hat{\theta}_1 \) exists and that \( R'_{L,H}(\hat{\theta}_1) > 0 \). Therefore, \( R_{L,H}(\hat{\theta}_1) > R_{L,H}(\hat{\theta}_1 - \epsilon) \) for a small \( \epsilon > 0 \).
strict concavity of the payoff function implies that there cannot be any mixed strategy equilibria. The, separating equilibria with pure strategies are characterized by conditions (23) and (24). These conditions implicitly define two cutoff values $\underline{\theta}_H$ and $\overline{\theta}_H$:

$$p(\theta_L^*)(1 - \phi \beta)\omega_L - \theta_L^*\chi = p(\overline{\theta}_H)(\omega_H - \phi \beta \omega_L) - \overline{\theta}_H\chi$$  \hspace{1cm} (27)

and

$$p(\underline{\theta}_H)(1 - \phi \beta)\omega_H - \underline{\theta}_H\chi = p(\theta_L^*)(\omega_L - \phi \beta \omega_H) - \theta_L^*\chi.$$  \hspace{1cm} (28)

Any $\theta_H' \in [\underline{\theta}_H, \overline{\theta}_H]$ is part of a separating equilibrium with asymmetric information. There are many possible beliefs that could rationalize any choice of $\theta_H' < \overline{\theta}_H$ in equilibrium. One possible set of beliefs could be the following: upon observing any tightness lower that $\theta_H'$, buyers believe that the submarket is populated by high-type capitalists only, and upon observing any tightness greater that $\theta_H'$, buyers believe that the submarket is populated by low-type capitalists only. Given such a set of beliefs, then high-type capitalists optimally choose tightness $\theta_H'$. From this example, we can see that those beliefs are not reasonable. The role of the IC is to eliminate equilibria with “unreasonable” beliefs, by imposing stronger requirements on off-equilibrium beliefs.

Consider all separating equilibria in which the low type chooses $\theta_L^*$ while the high type plays some $\theta_H' < \overline{\theta}_H$. Then, a tightness $\theta_H'' \in (\theta_H', \overline{\theta}_H)$ can be shown to be equilibrium-dominated for the low type but not for the high type. To show that $\theta_H''$ is dominated for the low type, consider how the payoff function for the low type pretends to be a high type varies with $\theta$. Defining these revenues as $R_{LH}(\theta) \equiv p(\theta)(\omega_H - \phi \beta \omega_L) - \theta LH\chi$. One can find the $\theta_LH$ that maximizes the revenues of the low type pretending to be the high type, by setting $\frac{\partial R_{LH}(\theta)}{\partial \theta} = 0$ (since $\omega_H - \phi \beta \omega_L > 0$, this is a strictly concave problem):

$$p'(\theta_LH)(\omega_H - \phi \beta \omega_L) = \chi.$$  \hspace{1cm} (29)

Then, it is enough to show that $\overline{\theta}_H < \theta_LH$, which implies that both $\overline{\theta}_H$ and $\theta_H''$ lie on the increasing part of the revenue function. Therefore, $\theta_H'$ must be dominated by $\overline{\theta}_H$. To show this, note that the

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Both conditions admit two solutions, however only one satisfies the constraint imposed by the single crossing condition of equilibria with asymmetric information (i.e. $\theta_L \leq \theta_L^*$). To see this in the case of condition (27), define the revenue function $R_{LH}(\theta) \equiv p(\theta)(\omega_H - \phi \beta \omega_L) - \theta LH\chi$. It can be easily seen that $R_{LH}(0) < p(\theta_L^*)(\omega_L - \theta_L^*\chi < R_{LH}(\theta_L^*))$, since the low type always has positive expected revenues. Thus, by continuity of the matching function, a solution to this equation exists. Additionally, the tightness that maximizes $R_{LH}(\theta)$ is greater than $\theta_L^*$. By strict concavity of $R_{LH}(\theta)$, this results implies that $R_{LH}'(\theta_L^*) > 0$. Therefore, condition (27) admits two solutions satisfying $\theta_L < \theta_L^* < \theta_2$, but only $\theta_1$ satisfies the single crossing property. To see this in the case of condition (28), define the revenue function $R_{HH}(\theta) \equiv p(\theta)(\omega_H - \phi \beta \omega_H) - \theta HH\chi$. It can be easily seen that $p(\theta_L^*)(\omega_L - \phi \beta \omega_H) - \theta LH\chi < R_{HH}(\theta_L^*)$, since $\omega_H > \omega_L$. In addition, since the single crossing property requires $\theta_H \leq \theta_L$, we have that $R_{HH}(\theta)$ for any $\theta \leq \theta_L^*$. Therefore, there exists at most one solution satisfying the single crossing condition and equation (28). If no solution exists (e.g., when $\omega_L < \phi \beta \omega_H$), then set $\overline{\theta}_H = 0$. 

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optimal choice for the low type when buyers detect the low quality of the capital unit is given by

\[ p'(\theta^*_L)(\omega_L - \beta \phi \omega_L) = \chi. \] (30)

Combining equations (29) and (30) we obtain

\[ \frac{p'(\theta^*_L)}{p'(\theta_LH)} = \frac{(\omega_H - \phi \beta \omega_L)}{(\omega_L - \phi \beta \omega_L)}. \]

Given that \( \frac{(\omega_H - \phi \beta \omega_L)}{(\omega_L - \phi \beta \omega_L)} > 1 \), it follows that \( \theta^*_L < \theta_{LH} \). Given that \( \overline{\theta}_H < \theta^*_L \), it follows that \( \overline{\theta}_H < \theta_{LH} \) and that \( R_{LH}(\theta''_H) < R_{LH}(\overline{\theta}_H) \).

Finally, we need to show that choosing \( \theta''_H \) is not a dominated strategy for the high type. To see this, solve for the \( \theta \) that maximizes the revenue of the high type under the assumption that buyers detect the high quality of the capital unit, which is given by \( R_{HH}(\theta) \equiv p(\theta)(\omega_H - \phi \beta \omega_H) - \theta \chi \) (again, since \( \omega_H - \phi \beta \omega_H > 0 \), this is a strictly concave problem). The market tightness that maximizes \( R_{HH} \) is given by

\[ p'(\theta_{HH})(\omega_H - \phi \beta \omega_H) = \chi. \]

Given that \( \overline{\theta}_H < \theta_{HH} \), any \( \theta''_H \in (\theta'_H, \overline{\theta}_H) \) lies in the increasing part of the revenue function. Then, it follows that \( R_{HH}(\theta'_H) < R_{HH}(\theta''_H) \). Given that the choice of market tightness \( \theta''_H \) is strictly dominated for the low type, but not for the high type, the IC requires that whenever buyers observe a capital unit being sold in submarket \( \theta''_H \), buyers must set a posterior belief \( \lambda_L \) to zero. But, in that case the capitalist with high quality would deviate. Since this argument applies for any \( \theta''_H \in (\theta'_H, \overline{\theta}_H) \), the unique separating equilibrium with asymmetric information that satisfies the IC is the one satisfying equation (27).

Proof of Corollary 2. From the single crossing property and the separating equilibrium obtained under the IC, we know that \( \theta_H < \theta_L \). Combining the expression for prices in the separating equilibrium we obtain

\[ q_H - q_L = \omega_H - \omega_L - \left( \frac{\chi}{\mu(\theta_H)} - \frac{\chi}{\mu(\theta_L)} \right), \]

and \( q_H > q_L \).

Proof of Proposition 4. Since \( q^P > q^A_L \) and \( \theta^P > \theta^A_L \), the capitalist with the low-quality capital is always better off in a pooling equilibrium. The next step is to show that this is also the case for the capitalist with the high-quality capital for a subset of the parameter space. This type of
capitalist is better off in a pooling equilibrium if and only if

\[ p(\theta^P)\bar{\omega} - \chi^P + (1 - p(\theta^P)) \phi\beta \omega_H \geq p(\theta_{H}^{AI})\omega_H - \chi_{H}^{AI} + (1 - p(\theta_{H}^{AI})) \phi\beta \omega_H, \]

where \( \bar{\omega} = \pi_L \omega_L + (1 - \pi_L) \omega_H \). Notice that \( \theta^P = \frac{\bar{\omega} - \chi^P}{(1 - \eta)(1 - \phi\beta)} \). Then, the previous condition can be rewritten as

\[ \left( \frac{\bar{\omega}}{\omega_H} \right)^{(1-\eta)/\eta} \left[ p(\theta_{H}^{FI}) (1 - \phi\beta) \omega_H - \chi_{H}^{FI} - p(\theta_{H}^{FI})\pi_L (\omega_H - \omega_L) \right] \geq p(\theta_{H}^{AI}) (1 - \phi\beta) \omega_H - \chi_{H}^{AI}. \] (31)

Finally, notice that

\[ \lim_{\pi_L \to 0} \left( \frac{\bar{\omega}}{\omega_H} \right)^{(1-\eta)/\eta} \left[ p(\theta_{H}^{FI}) (1 - \phi\beta) \omega_H - \chi_{H}^{FI} - p(\theta_{H}^{FI})\pi_L (\omega_H - \omega_L) \right] \] (32)

\[ = p(\theta_{H}^{FI}) (1 - \phi\beta) \omega_H - \chi_{H}^{FI} > p(\theta_{H}^{AI}) (1 - \phi\beta) \omega_H - \chi_{H}^{AI}. \] (33)

and

\[ \lim_{\pi_L \to 1} \left( \frac{\bar{\omega}}{\omega_H} \right)^{(1-\eta)/\eta} \left[ p(\theta_{H}^{FI}) (1 - \phi\beta) \omega_H - \chi_{H}^{FI} - p(\theta_{H}^{FI})\pi_L (\omega_H - \omega_L) \right] \] (34)

\[ = p(\theta_{L}^{AI}) (\omega_L - \phi\beta \omega_H) - \chi_{L}^{AI} < p(\theta_{H}^{AI}) (1 - \phi\beta) \omega_H - \chi_{H}^{AI}. \] (35)

The inequality in equation (33) follows from the fact that \( \theta_{H}^{FI} = \argmax_{\theta} p(\theta) (1 - \phi\beta) \omega_H - \chi \theta \). The inequality in equation (35) follows from the definition of the separating equilibrium that satisfies the IC, that requires that the high-type capitalist does not want to mimic the low-type capitalist. Then, by continuity and strict monotonicity of the left hand side of equation (31), there exists a \( \pi_L \) such that

\[ \left( \frac{\omega_H - \pi_L (\omega_H - \omega_L)}{\omega_H} \right)^{(1-\eta)/\eta} \left[ p(\theta_{H}^{FI}) (1 - \phi\beta) \omega_H - \chi_{H}^{FI} - p(\theta_{H}^{FI})\pi_L (\omega_H - \omega_L) \right] = p(\theta_{H}^{AI}) (1 - \phi\beta) \omega_H - \chi_{H}^{AI}. \]

Then, for \( \pi_L \leq \pi_L \) the high-quality capitalist is better off in a pooling equilibrium than in the separating equilibrium satisfying the IC, and the pooling equilibrium is a Pareto improvement. ■
Online Appendix

A Data Appendix

A.1 The online platform

This subsection quickly introduces how the platform works. When entering the website, the buyer encounters the screen shown in Figure A.1. The platform asks the client to choose a type of transaction (buy, rent, or find a shared space), the type of property (retail store, office, etc.), and the location.

**Figure A.1: Main Website**

Once those options are selected, suppose the client chooses to find a unit in Madrid (Figure A.2). There, the website shows the number of properties available for sale by area of the city.

**Figure A.2: Options Madrid**

After choosing a more narrowed location (not shown here), the client finds a scroll list of the available units that meet her requirements, as shown in Figure (A.3). There the user can include more filters depending on her requirements for layout and amenities.
When the user finds a unit that may be to her taste and clicks on it, the website pops up a window with the details shown in Figure A.4 plus text detail not shown here. The main information the post contains is the unit description with pictures, the price, the change in price, the area, the date of construction, and other amenities and equipment.
A.2 Representativeness of the dataset

In this subsection, we analyze the representativeness of the dataset, showing that our data is consistent with aggregate patterns observed in Spain over this period. We provide two pieces of evidence about our data. First, we show that in our data, the price index exhibits the patterns of aggregate data, with a difference in timing, with our data leading the aggregate indexes. Second, we show that the patterns of sales follow those of aggregate sales of structures in Spain.

Figure A.5 shows the price index for properties for sale in our sample, and the home price index of Spain. Both indexes are normalized to take the value of 1 in the first quarter of 2007. We highlight that the fall in prices we observe is consistent, and very similar in size to that observed for houses in Spain during the recent financial crisis. Moreover, our index leads the aggregate index, which makes intuitive sense when we consider that our index consist of posted prices, that will take some months from exiting the database to be registered as sales and recorded in national statistics.

Figure A.6 shows the sale index for properties for sale in our sample and the home price index of Spain. Both indexes are normalized to take the value of 1 in the first month of 2007. The index for our data is constructed by computing the share of units that exit the database with respect to the number of active posts in that month. In the case of the aggregate number, we normalize the number of sale transactions recorded by the Statistical Agency. In doing this, we assume that the total stock of units during this period is fairly constant, since we do not have the size of the stock. Although our numbers are more noisy than the national estimates, the patterns of the two series
are close to each other.

**Figure A.5: Price Index: Dataset versus Aggregate Data**

![Price Index Chart]

*Note:* The solid line shows the price index for properties for sale in our dataset. The dashed line shows the aggregate real estate price index gathered from the Statistical Agency of Spain (INE). Both indexes take the value of one in the first quarter of 2007.

**Figure A.6: Sales Rate: Dataset versus Aggregate Data**

![Sales Rate Chart]

*Note:* The solid line shows the sales rate for properties in our dataset. The dashed line shows the aggregate sales index of real estate gathered from the Statistical Agency of Spain (INE). Both indexes take the value of one in January, 2007.