Is squatting a good business for the security industry? A case analysis from Spain

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ABSTRACT

The aim of this paper is to analyze the relation between the rise of the squatter movement in Spain and the evolution of firms involved into the security and surveillance business. We hypothesize that the upsurge of this phenomenon might benefit the evolution of these companies. Using Google searches to measure the citizens' attention and concerns to the squatter movement, we analyze their impact on the evolution of the unique security company listed in the Spanish stock market: Prosegur. The empirical analysis points out to a positive and significant relationship, which is robust to the inclusion of other market variables. Moreover, we find out that this relationship disappears or turns negative for other types of firms and for the stock market in general, suggesting that our measure of attention to the squatter movement might actually be a proxy for an impairment of the rule of law in Spain.

Keywords: Squatter movement, security business, Google searches, Prosegur, stock markets.

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1. INTRODUCTION AND THEORETICAL BACKGROUND

The squatter movement in Spain, born in the second half of the twentieth century, namely in the early 80s (Martínez, 2007), is becoming a growing concern for Spanish citizens. Thus, the squatter movement has gained popularity in Spain, especially at the dawn of the financial crisis of 2008 and the more recent COVID-19 crisis as an alternative that provides the possibility of finding a household. According to data from *EPdata*[1], the number of occupations boosted from 10,376 in 2015 to 14,621 in 2019, an increase of 40.9%. Moreover the, new eviction law, enacted in 2018, has not showed a reduction in the number of occupations and during the first semester of 2020 there has been 7,450 occupations, a 5% more than in the same period of 2019. The data indicate that most of those occupations are related to empty households that belong to financial corporations or real estate investment companies, but the reality is that society is becoming more and more concern about this phenomenon. Accordingly, we assume that the rise of the squatter movement leads to a worsening in the security perception from citizens, since it directly affects the effectiveness of legal measures to defend property rights between private agents which, according to Ouattara and Standaert (2020), is one of the main indicators of property rights.

Thus, citizens, who are increasingly concerned about this phenomenon, attempt to better protect their household. Hence, it is not surprising that more and more households are getting equipped with protection or surveillance systems to protect them against the entrance of squatters[2]. Considering this, in this paper we examine whether the attention

[1] https://www.epdata.es/datos/denuncias-okupacion-graficos/560.

[2] See for instance this piece of news according to which the alarm business in second households has boosted due to the fear to squatters: https://www.elespanol.com/invertia/observatorios/vivienda/20200723/miedo-okupas-relanza-negocio-alarmas-segundas-residencias/507200340_0.html.

or concern to the squatter movement phenomenon has something to do with the evolution of the shares of firms which main activity is to provide security services as well as protection or surveillance systems. Namely, we use internet searches gathered from Google Trends to obtain a high frequency measure of the attention or concern related to the squatter movement and we gather the evolution of the stock price of the company Prosegur, which main activity is providing these protection and surveillance systems and that is the only one listed in the Spanish stock market.

Regarding Google data, they have demonstrated their capacity to proxy users' attention to different phenomena in different fields of study (Baur and Dimpfl, 2016; D'Amuri and Marcucci, 2017; Da et al., 2011, 2015; Gao et al., 2020; Ginsberg et al., 2009; Niesert et al., 2020; Solano et al., 2016). Moreover, Google Trends have shown a great ability to proxy private consumption (Vosen and Schmidt, 2011). More related to the particular aim of this paper, Google data have been useful to measure the impact of given events on financial assets, either they are positive or negative. In this sense, there are several examples in which authors have demonstrated the relationship between Google searches related to a specific event and the stock market in general. For instance, the recent COVID-19 crisis is a clear example of this and several works (Costola et al., 2020; Lyócsa et al., 2020, among others) have shown that an increase of Google attention to the pandemic negatively affects the stock and financial markets in general. For weather, economic, geopolitics and diseases events, Fernández-Perez et al (2020) study the impact on commodities futures prices of them measured through their attention on Google searches. For instance, a greater attention to a cold spell would increase the price of natural gas or oil, while attention to hurricanes would increase the price of lumber. On the other hand, a greater attention to a heavy drought can increase the price of seeds.

Similarly, we expect that Google searches allow us to accurately measure the attention to a specific event: the squatter movement in Spain, and we relate this variable with the evolution of an individual firm: Prosegur. We hypothesize that a greater attention or concern about the squatter movement, i.e., a larger number of Google searches related to it, leads to a surge in the price of the shares of the firm. The empirical results allow us to confirm this hypothesis. Moreover, the results are robust to the inclusion of control variables and the placebo test performed points out that the relationship we find is not random or accidental.

Thus, the contribution of the paper is threefold. First, to the best of our knowledge, our paper is the earliest attempt to link the probable influence of the squatter movement on the evolution of security industry. Second, we propose a novel and high frequency proxy based on Google Trends data to measure the attention related to the squatter movement, rather than other proxies or indicators based on low frequency surveys. Third, we empirically demonstrate that this proxy shows a significant and positive impact on the shares of a concrete security firm: Prosegur.

The remainder of the paper unfolds as follows; next section describes the data and methodology; section 3 summarizes the main results and section 4 concludes the paper.

2. DATA AND METHODOLOGY

The aim of the paper is to analyze whether the internet attention regarding the squatter movement in Spain, proxied through Google searches, shows a positive relationship with the evolution shares of listed companies in the security sector. For this purpose, first we look for security firms in Madrid stock market index. We find there is only one listed firm in the security sector: Prosegur. We gather the adjusted close prices of the firm at a weekly frequency from January 2011 until December 13th, 2020.

In regards to the internet attention related to the squatter movement, we select the Spanish keyword *ocupa*[3]. According to Dzielinski (2012), the keyword must be specific enough to contain no or small noise which must be constant over time and not be used to describe other concept[4]. Moreover, it is recommended to use the most frugal keyword (Vozlyublennaia, 2014). We consider that keyword *ocupa* meets all these requirements. Google takes into account the fact that users might search for the same keyword repetitively, so that behaviour are removed from the data to avoid manipulation (Jun et al., 2016). We gather the weekly data from Google Trends website[5] for this keyword for the same time span than for Prosegur stock price. We narrow the searches to those performed in Spain. These Google series are commonly denoted as GSVI (Google Search Volume Index, hereinafter)[6]. The election of weekly data provides several advantages. First, Google Trends daily data can be excessively noisy since Google only provides daily data for a maximum length of eight months. That would require downloading multiple blocks of data and merging them to cover a longer time span. Moreover, weekly data is expected to better reflect the dynamics of users' attention than lower data frequencies, such as monthly frequency.

Furthermore, since the frequency of the dataset is weekly, it is worth noting that Google does not allow gathering more than five years of data at a weekly frequency for

[3] We consider that this keyword represents the colloquial form in which people would search for this phenomenon.

[4] It is worth noting that *ocupa* has other meanings in Spain, but we have checked the related keywords, i.e., those keywords for which people who searched for *ocupa* also searched for, and the most related keyword is *okupa* which is, incontrovertibly, related to the squatter movement. Therefore we assume that most of the searches for *ocupa* are related to the squatter movement. We have also considered other potential keywords, such as that informal form *okupa*. However, Google Trends provide a time series with many zeros for this term.

[5] See Stephens-Davidowitz and Varian (2015) for a deeper analysis of how Google Trends data work

[6] Google data might slightly differ depending on the date in which they are downloaded. This is due to the fact that Google uses a random sample of all searches to calculate the GSVI and that random sample varies every day. This matter has been spotted by several authors (Carrière-Swallow and Labbé, 2013; Da et al., 2011, 2015). To check it we have downloaded the data on two different dates and calculated the correlation of both series. It is over 95% so we assume that this issue does not affect our data or is just residual.

a given keyword. Therefore to cover our time span (2011-2020) we need to download two blocks of five years data each and then combine them into a single series. This creates a problem which is that every downloaded period has a maximum of 100 since those blocks of data are independent from each other.

Therefore, when we combine the two blocks of weekly data into a single series we get a series with two peaks at 100 and a jump or a drop in the data when both blocks joint (between 2015 and 2016). To solve this, we follow Kostopoulos et al.(2020) procedure, i.e., we use the monthly time series, which are available for the whole period (January 2011-December 2020), to rescale the weekly series. To illustrate this, in Figure 1, left graph, we show the raw weekly series of the GSVI for the keyword *ocupa*. We can observe that there are two maximum peaks at 100 as expected. Then, we download the GSVI for the same time period at a monthly frequency (Figure 1, right graph). We can observe that the monthly data show only one maximum of 100.

[Insert Figure 1 around here]

The next step is to transform our two blocks of weekly data into a single series of rescaled weekly data using the monthly time series. Specifically, the weekly data for each week is multiplied by the respective monthly search interest and then divided by 100 (Kostopoulos et al., 2020). Hence, the raw weekly GSVI is converted into a rescaled GSVI as shown in Figure 2, in which there is only one maximum close to 100 which matches with the maximum point of the monthly series.

[Insert Figure 2 around here]

Once we have the rescaled the weekly series, the rescaled GSVI is converted into logarithms as in Da et al. (2011) or Vozlyublennaia (2014), among others. We also

transform into logarithms Prosegur stock price. Figure 4 shows the evolution of both time series in logs. We can guess that they show a similar evolution. However, this pattern stops as a consequence of the COVID-19 pandemic on March 2020. Therefore, to control for this sharp drop that has nothing to do with the squatter movement, but is driven by the financial dynamics occurred after the pandemic, we create a COVID-19 dummy variable to capture this market crash since. This variable takes the value one after the first week of March 2020, and zero otherwise. Moreover, we also include in some of the specifications the general stock market indexes of Spain to control for this shock. A summary of the variables included in the analysis along with their source is shown in Table 1.

[Insert Figure 3 around here]

Regarding the methodology, we first run some regressions using Prosegur stock price as dependent variable as shown in equation 1, where $GSVI_t$ represents the Google Search Volume Index after the rescaling procedure, and $Controls_t$ is a set of control variables which includes a dummy variable to control for the COVID-19 pandemic, the evolution of Spanish stock market and Prosegur stock traded volume and ε_t is the error term.

$$Prosegur\ stock\ price_t = \alpha + \beta_1 GSVI_t + \beta_2 Controls_t + \varepsilon_t \qquad (1)$$

For robustness purposes we also run some rolling regressions to check the historical relationship between our keyword and Prosegur stock price. Moreover, we have also checked other potential keywords that, although are not related to the squatter movement itself as the keyword *ocupa*, are related to insecurity concerns or directly related to the installation of security and surveillance systems. We expect that these new keywords maintain the positive relation to Prosegur stock price.

[Insert Table 1 around here]

Furthermore, we also run a placebo test in order to check whether the relationship between Prosegur stock price and the GSVI for *ocupa* remains or not for other kind of companies which business is not related to security and surveillance. Ex-ante expectations suggest that whether the increase in the price of Prosegur is explained in part due to an upsurge on the squatter movement and insecurity issues reflected on the attention to them, the same analysis for the general stock market or other compaies (energy companies, banks, for instance) will not show the expected positive relationship between the GSVI for *ocupa* and their stock prices. Thus, we select an example of these companies and general stock market indexes: an energy company (*Repsol*), a bank (*Banco Santander*), the general stock market index in which Prosegur quotes (IGBM) and the Spanish main stock market index (IBEX-35) to test this hypothesis.

3. RESULTS

3.1. Do Google searches related to squatter movement in Spain influence *Prosegur* stock price?

To test this postulation, we run some regressions using Prosegur stock price as dependent variable to check the influence of Google searches on it. The results from the regressions are shown in Table 2.

[Insert Table 2 around here]

Model 1 includes the GSVI alone. We can observe that it shows the expected positive sign but the coefficient is not significant. We assume that this is due to the fact that during the last part of the sample, which covers the COVID-19 pandemic, the relationship between both variables is distorted because of the pandemic. To check this,

in Model 2 we considered the time series until the last week of February[7] to remove the pandemic effect. We can observe that, with this procedure, the coefficient turns highly significant confirming our expectations. Moreover, in model 3 we include the dummy variable which captures the effects of the COVID-19 and, therefore, we avoid reducing the sample. This dummy variable shows the assumed negative sign and its inclusion barely affects the coefficient of the GSVI from Model 2. In the next models we include several control variables related to the stock market itself to check whether their inclusion reduces or removes the significance of Google searches. Namely, we include the negotiated volume of shares of *Prosegur* in Model 4 along with the COVID-19 dummy and in the last three models we include the adjusted close price of the IGBM and the IBEX-35 to control for the general evolution of the Spanish stock market. These variables are likely to capture the same effect of the COVID-19 dummy, so we do not include all of them together in the same model to avoid autocorrelation issues. Note that the inclusion of these controls reduces the value of the coefficient of the GSVI although the positive sign and significance remain stable as we aim to demonstrate.

3.1.1 Analysing the historical relationship between the GSVI for the keyword *ocupa* and Prosegur stock price

To be exhaustive in the analysis, we also performed some rolling regressions to check the historical relationship between the GSVI for the keyword *ocupa* and Prosegur stock price. Hereof, we run a rolling regression for each of the models from Table 2 starting the first regression at observation *t=1* and finishing at observation *t=100*. Then, we add one observation each time keeping constant the starting point. Consequently, the second regression will cover the period between *t=1* and *t=101*. We repeat this procedure up to

[7] The World Health Organization officially declared the pandemic on March 11th, 2020, and, before, on January 30th, 2020, they had already declared the COVID-19 as a public health emergency of international concern.

the end of the sample which will give us 419 regressions (with the exception of model 2, which gives us 376 regressions). This iterative process allows us to know the historical relationship between both variables and check whether it has remained positive and significant along all the time series.

Once we have performed all this regressions we calculate the mean value of the coefficient for the GSVI and the robust standard error. We expect that the former remains positive and significant. The results are shown in Table 3. We can observe that the coefficient is positive and highly significant for all of the models, even for Model 1, since the historical relationship absorbs the pandemic effect that removes the significance from Model 1, Table 2.

[Insert Table 3 around here]

In short, we have proven that there exists a positive relationship between citizen's attention to the squatter movement, measured through the GSVI for the keyword *ocupa* and the evolution of Prosegur stock price. This relationship remains significant regardless the inclusion of control stock market variables and is also confirmed by the rolling regressions which verify the positive and significant historical relationship.

3.2 Does this effect remain for other potential keywords?

We have focused on the possible positive effects that the concerns about the squatter movement might have on the stocks of a security firm. Nonetheless, somebody might argue that the keyword *ocupa* is not reflecting the actual perception related to the squatter movement or maybe other keywords, not directly related to that phenomenon, but directly related to system and surveillance systems might have a greater influence on Prosegur stock price. In this sense, we have selected eight keywords such as: *alarma*

casa, alarma hogar, camara de seguridad, instalar alarma, ocupacion vivienda, poner alarma, sistema de alarma and *videovigilancia*[8]. The choice of this keywords is arbitrary but keeping in mind to select the most parsimonious term possible (Vozlyublennaia, 2014). For each of the keywords we have downloaded the GSVI for the period between January 2011 and December 13th, 2020 and rescaled those weekly data using the monthly data for the same period, as we did for *ocupa,* following Kostopoulos et al. (2020) methodology. Then, the time series are converted into logarithms.

[Insert Table 4 around here]

Table 4 shows the pairwise correlations between the initial keyword, *ocupa,* and these new keywords. We appreciate that our initial keyword, *ocupa,* shows a positive and significant correlation with all the new keywords, with the exception of *videovigilancia* which exhibits a negative and not significant correlation with most of them. Subsequently, to check whether the attention to these keywords also have an impact on Prosegur stock price, we run a rolling regression procedure[9], as we did in the previous section, to check the historical relationship between these new keywords and Prosegur stock price following equation (2) where j represents the new keywords $j = 1, 2 \dots 8$.

$$Prosegur\ stock\ price_t = \alpha + \beta_1 GSVI_{j,t} + \varepsilon_t \qquad (2)$$

We expect that these keywords show a positive and significant relationship to Prosegur stock price. The results for these rolling regressions are shown in Table 5. We

[8] The selection of these keywords is We have discarded the simple keyword *alarma* since searches for it are biased because of the expression *estado de alarma* which has nothing to do with the aim of the paper and experimented a sharply increase during the pandemic.
[9] We have also performed the rolling regressions including control variables and the results do not differ from those reflected on Table 5.

observe that all the keywords show a positive and significant historical relationship with the exception of the keyword *videovigilancia*. Moreover, the keyword that seems to have a greater influence on Prosegur stock price is *camaras de seguridad*. It exhibits an average GSVI coefficient of 0.184 which is, by far, the largest one among all keywords.

[Insert Table 5 around here]

Afterwards, we run some regressions considering the whole time series for each of the new keywords and including control variables as shown in Table 6. The results confirm that the keyword *camaras de seguridad* is the one that shows the greatest impact on Prosegur stock price. Its coefficient is 0.159 which is even higher that for the keyword *ocupa* in the same model specification (Model 6, Table 2) which is 0.057. Also other keywords, such as *instalar alarma, ocupacion vivienda, poner alarma* and *sistema de alarma*, reveal a positive and significant coefficient to Prosegur stock price.

[Insert Table 6 around here]

Overall, we can confirm that the citizens' attention to the squatter movement in particular and to insecurity concerns in general, which might be indirectly related to the squatter movement, has a positive impact on the evolution of Prosegur stock price.

3.2.1. Which is first: the GSVI for the keyword *ocupa* or the GSVI for the rest of keywords?

In this section we attempt to determine whether the concern about the squatter movement, measured through the GSVI for the keyword *ocupa*, leads to an increase in the searches of other relevant keyword: *camaras de seguridad*[10], or whether it is the

[10] For consciousness, we have only reported the results for this keyword. However, we have performed the same analysis for the rest of keywords and we have found similar results, i.e., that the GSVI for the

opposite, i.e., that the GSVI for *camaras de seguridad* drives the GSVI for *ocupa*. Whether it is the former, we can allege that the GSVI for the keyword *camaras de seguridad* is also indirectly related to the squatter movement since it is driven by the keyword *ocupa*. To check this idea, we run a VAR model between both variables. First we run this methodology choosing a large and arbitrary number of lags $p=8$ to check which is the optimal number of lags. According to Akaike's criteria (AIC) the optimal lag length is $p=4$ (AIC=2.1517). The results are shown in Table 7.

[Insert Table 7 around here]

Note that in the second column, which represents the equation for the GSVI for *ocupa*, only the fourth lag for the GSVI for *camaras de seguridad* is positive and significant. On the other hand, whether we focus on the third column, which is the VAR equation for the GSVI *camaras de seguridad,* we observe that the first two lags of the GSVI for the keyword *ocupa* are positive and significant, while the third lag is also significant but negative. This indicates that the first two past observations for *ocupa* lead to an increase in the GSVI for *camaras de seguridad* while an increase in the GSVI for *ocupa* three weeks before would produce a decrease in the GSVI for *camaras de seguridad* in the current week. Accordingly, it seems that the GSVI for *ocupa* has a greater impact on the GSVI for *camaras de seguridad* that the other way around. In panel B we confirm this hypothesis performing a Granger causality test. The result indicates that the GSVI for the keyword *ocupa* Granger-causes the GSVI for the keyword *camaras de seguridad.*

In brief, with this we have demonstrated that the attention to the keyword *ocupa* is the leading indicator for other keywords. Therefore, they are the concerns about the

keyword *ocupa* Granger-causes the GSVI of the rest of keywords. For the keywords *alarma casa*, *ocupacion vivienda* and *poner alarma* we have found a reverse Granger causality.

squatter movement those which lead to perform other searches directly related to surveillance and vigilance systems that might also impact on Prosegur stock price.

3.3. Placebo test

One question which might arise is whether the positive and significant relationship shown in the previous sections between the GSVI for the keyword *ocupa* and Prosegur stock price might be due to a spurious connection and is not reflecting actual concerns or attention about the occupation of households and the subsequent interest for security and surveillance systems, which would have a positive impact on Prosegur's share price. To check this point we reproduce similar regressions to those performed in section 3.1, but now we use IGBM, IBEX-35, Banco Santander and Repsol adjusted close price as dependent variables. Whether the relationship between the GSVI for the keyword *ocupa* and Prosegur stock price is just spurious, we would expect that Google searches would also show a significant impact on those indexes and shares in the same direction than for Prosegur.

In Table 8 we show the results for this placebo test. We can observe that the coefficient for the GSVI varies between a negative and significant sign and a positive and insignificant sign in the estimations. We cannot appreciate here the solid pattern that we observe in Tables 2 and 3 regarding Prosegur. In light of these results, we can confirm that the relationship between the GSVI for the keyword *ocupa* and Prosegur stock price is not random or spurious, but it relies on an actual relation. Moreover, this finding might have other interesting and notable implications, i.e., that the GSVI for the keyword *ocupa* is a proxy of the rule of law in Spain. Thus, it is expected that it relates negatively to the stock market indexes and other shares whose business does not take any benefit from the occupation of households or from security concerns. Therefore, it

seems that the GSVI for the keyword *ocupa* is somehow measuring the effectiveness of authorities related to the protection of household property rights.

[Insert Table 8 around here]

Hence, an increase in the GSVI represents a drop in the rule of law[11] of the country through the worsening of property rights. This is consistent with the fact that the GSVI positively affects Prosegur since that kind of firms are expected to benefit whether citizens perceive an increase in insecurity in the country and a worsening of the rule of law.

4. CONCLUSIONS

In this paper we have analyzed how concerns of the Spanish population about the squatter movement leads to an increase in the price of companies whose business is focused on providing security and surveillance systems. To empirically check this idea, we select a firm which is listed in the Spanish stock market, Prosegur, and analyze the impact that the number of Google searches related to the squatter movement, specifically, for the keyword *ocupa*, has on the price evolution of the shares of that company.

Our findings suggest that, indeed, there is a positive relationship between both variables. Therefore, an increase in the concerns about the squatter movement, which is reflected as an increase on Google searches, leads to an upsurge in Prosegur's stock price. Moreover, this relationship is robust to the inclusion of other market measures and to the selection of other keywords. Moreover, we have demonstrated that it is the keyword *ocupa* the one which drives the searches for other keywords related to security

[11] We have calculated the annual average of the GSVI for the keyword *ocupa* and measured its correlation to the Spanish Rule of Law index from World Governance Indicators (WGI) and it is -80% (2004-2019), suggesting a negative and significant relationship.

or insecurity. Furthermore, it is worth noting that we have also addressed a placebo analysis to test whether this relationship keeps for other kind of firms or for the Spanish stock market in general. The results are quite conclusive: we have not found that positive relationship, actually, we obtained the opposite. We argue that this reveals that Google searches related to the squatter movement may be, not only measuring the concern about that concrete phenomenon, but also a measure of the deterioration of property rights and the rule of law. We expect to develop this hypothesis in further studies, but we have laid the foundations for this in the current paper

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Figure 1

The figure plots Google Search Volume Index (GSVI) for the keyword *ocupa*. The left graph shows the weekly searches and the right graph the monthly searches. Both graphs cover the period between January 2011 and December 13th, 2020.

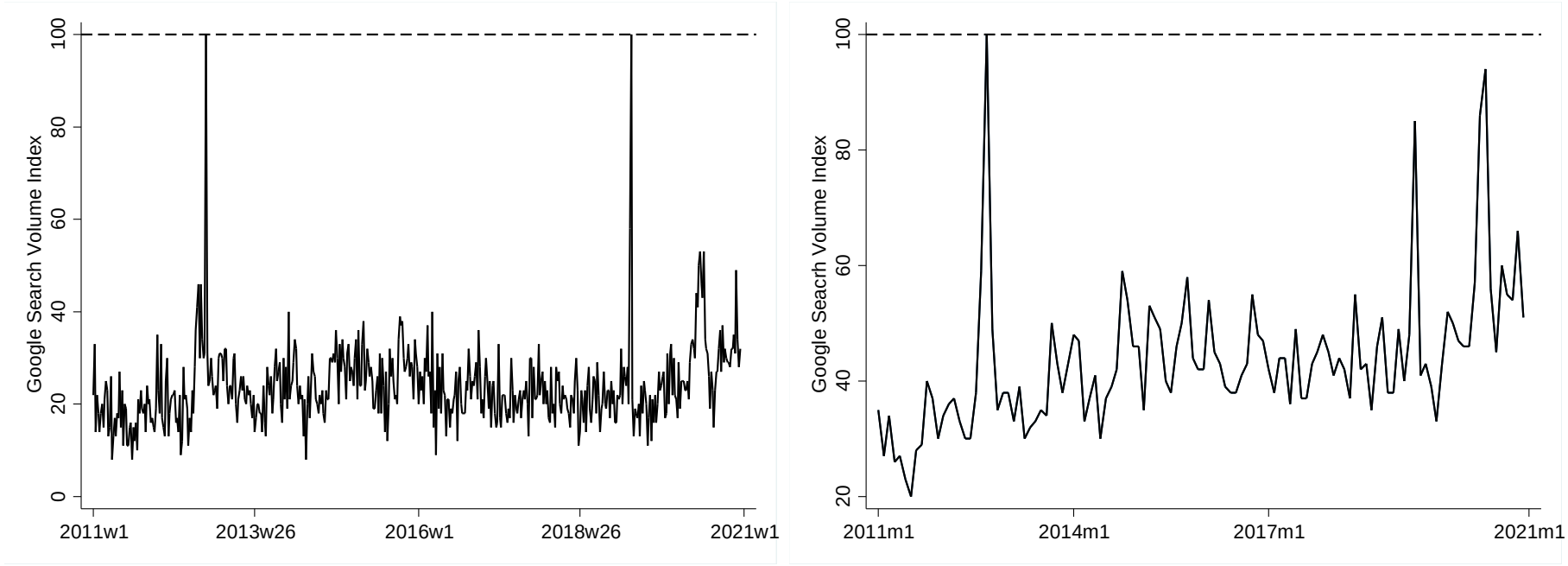

Figure 2

The graph plots the evolution of the rescaled Google Search Volume Index (GSVI) for the keyword *ocupa* for the period between January 2011 and December 13th, 2020. The rescaling has been performed using the monthly series as reference.

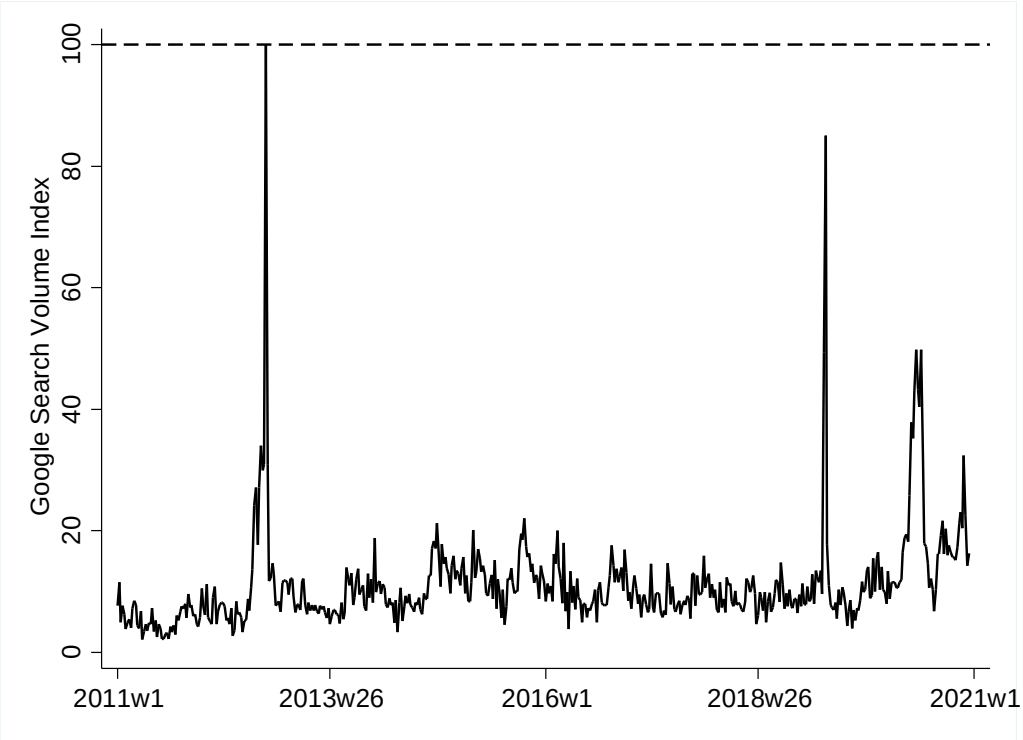

Figure 3

The graph plots the evolution of our both series of interest: rescaled Google Search Volume Index (GSVI) for the keyword *ocupa* (dot line) and Prosegur stock price (solid line) both in logs. The time horizon encompasses the period between January 2011 and December 13th, 2020.

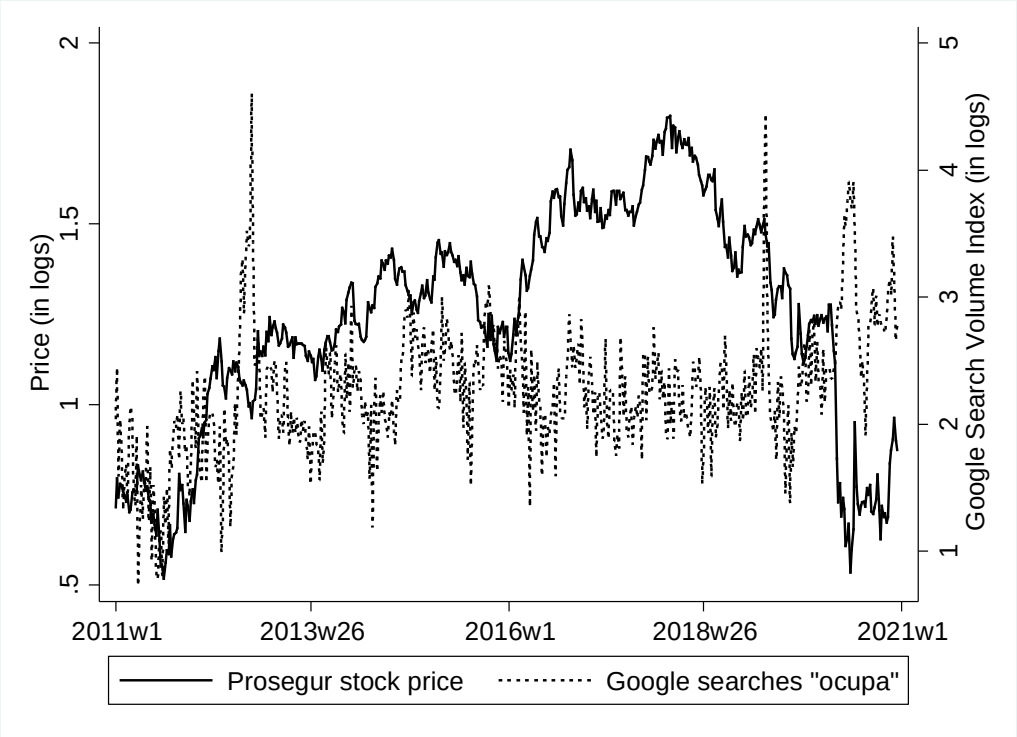

Table 1. Variables included in the study

The table shows the variables included in the analysis along with a brief description and the data source form which they have been obtained

Variable	Description	Source
Dependent variable		
Prosegur stock price	Time series of Prosegur adjusted close stock price	Yahoo finance
Variables of interest		
GSVI (*ocupa*)	Time series of the Google Search Volume Index for the queries performed in Spain for the keyword *ocupa.*	Google Trends
GSVI (other keywords)	Time series of the Google Search Volume Index for the queries performed in Spain for the following keywords: *alarma casa, alarma hogar, camara de seguridad, instalar alarma, ocupacion vivienda, poner alarma, sistema de alarma* and *videovigilancia*	Google Trends
Control variables		
Volume Prosegur	Volume of negotiation of Prosegur stocks	Yahoo finance
IGBM	Evolution of the "*Índice General e la Bolsa de Madrid"* close price, which is the Spanish index in which Prosegur is included	Investing.com
IBEX-35	Evolution of the IBEX-35 index adjusted close price, which is Spanish main stock index.	Yahoo finance
COVID-19 dummy	Dummy which takes the value after March 2020 (COVID-19 pandemic) and 0 otherwise	Own elaboration
Placebo variables		
Repsol stock price	Time series of Endesa adjusted close stock price	Yahoo finance
Banco Santander stock price	Time series of Banco Santander adjusted close stock price	Yahoo finance

Table 2. Regression analysis

The table shows the regressions using Prosegur adjusted stock price in logs as dependent variable. *GSVI ocupa* represents the rescaled Google Search Volume Index for the keyword *ocupa*. *Dummy* is a variable which takes the value one after March 2020, to control for the COVID-19 pandemic, and zero otherwise. *Volume* shows the negotiated volume of Prosegur. *IGBM* and *IBEX-35* display the close price in logs of the Spanish indexes. The estimation period covers the time horizon form January 2011 to December 13th, 2020 with the exception of Model 2 which concludes in February 23rd, 2020 (before the COVID-19 pandemic). Robust standard errors are shown in parentheses. *, ** and *** denote significance at 10%, 5% and at 1%.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
GSVI *ocupa* (in logs)	0.024	0.198***	0.177***	0.156***	0.079***	0.057**	0.051**
	(0.035)	(0.035)	(0.033)	(0.031)	(0.028)	(0.025)	(0.025)
Dummy crisis			-0.670***	-0.657***			
			(0.034)	(0.035)			
Volume *Prosegur* (in logs)				-0.101***		-0.145***	-0.143***
				(0.017)		(0.016)	(0.016)
IGBM (in logs)					1.077***	1.152***	
					(0.076)	(0.073)	
IBEX-35 (in logs)							1.182***
							(0.076)
Constant	1.184***	0.846***	0.891***	2.453***	-6.301***	-4.581***	-7.507***
	(0.081)	(0.081)	(0.075)	(0.258)	(0.522)	(0.531)	(0.713)
N	518	476	518	518	518	518	518
R^2	0.001	0.105	0.294	0.336	0.248	0.334	0.329
F-stat	0.46	30.42	236.12	145.64	106.20	98.65	96.34
RMSE	0.306	0.265	0.258	0.250	0.266	0.251	0.252

Table 3. Rolling regressions

The table shows the rolling regressions using Prosegur adjusted stock price in logs as dependent variable. We realize a one week expanding window procedure. The first regression starts at week *t=1* and ends at week *t=100*. We keep constant the beginning of the period and move one week ahead the end of the time horizon (*t=518* weeks), therefore we add one observation in each regression. We report the average coefficient for the Google Search Volume Index (GSVI) and the average robust standard error. *, ** and *** denote significance at 10%, 5% and at 1%.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
GSVI Coefficient	0.192***	0.204***	0.200***	0.176***	0.181***	0.155***	0.155***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.034)	(0.033)	(0.033)
Number of regressions	419	376	419	419	419	419	419

Table 4. Correlations between keywords

The table shows the pairwise Pearson's correlations between the rescaled Google Search Volume Index (GSVI) in logs for the keywords that are displayed in the first column in italics for the period between January 2011 and December 13th, 2020. *, ** and *** denote significance at 10%, 5% and at 1%.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
Ocupa (1)	1.000								
Alarma casa (2)	0.319***	1.000							
Alarma hogar (3)	0.190***	0.242***	1.000						
Camaras de seguridad (4)	0.165***	0.080*	0.003	1.000					
Instalar alarma (5)	0.174***	0.152***	0.040	0.122***	1.000				
Ocupacion vivienda (6)	0.152***	0.131**	0.006	0.121***	0.097**	1.000			
Poner alarma (7)	0.343***	0.329***	0.179***	0.277***	0.167***	0.191***	1.000		
Sistema de alarma (8)	0.282***	0.195***	0.108**	0.081*	0.079*	0.106**	0.248***	1.000	
Videovigilancia (9)	-0.055	-0.095**	-0.042	0.096**	-0.030	-0.002	-0.130***	0.002	1.000

Table 5. Rolling regressions for other keywords

The table shows the rolling regressions using Prosegur adjusted stock price in logs as dependent variable. As explicative variables we use the Google Search Volume Index (GSVI) of the keywords shown in the first row. We apply a one week expanding window procedure. The first regression starts at week *t=1* and ends at week *t=100*. We keep constant the beginning of the period and move one week ahead the end of the time horizon each time until *t=518* weeks. We report the average coefficient for the GSVI and the average robust standard error in parentheses. *, ** and *** denote significance at 10%, 5% and at 1%.

	Alarma casa	*Alarma hogar*	*Camaras de seguridad*	*Instalar alarma*	*Ocupacion vivienda*	*Poner alarma*	*Sistema de alarma*	*Videovigilancia*
GSVI Coefficient	0.036***	0.012**	0.184***	0.014***	0.016***	0.051***	0.012***	-0.008
	(0.007)	(0.005)	(0.022)	(0.004)	(0.004)	(0.006)	(0.004)	(0.021)
N. of regressions	419	419	419	419	419	419	419	419

Table 6. Regression analysis for other keywords

The table shows the regressions using *Prosegur* adjusted stock price in logs as dependent variable. *GSVI* represents the rescaled Google Search Volume Index for the keywords shown in the first row. *Volume* shows the negotiated volume of *Prosegur*. *IGBM* displays the close price of the Spanish index in which Prosegur quotes. The estimation period covers the time horizon form January 2011 to December 13th. Robust standard errors are shown in parentheses. *, ** and *** denote significance at 10%, 5% and at 1%.

	Alarma casa	*Alarma hogar*	*Camaras de seguridad*	*Instalar alarma*	*Ocupacion vivienda*	*Poner alarma*	*Sistema de alarma*	*Videovigilancia*
GSVI (in logs)	0.008	0.001	0.159***	0.009***	0.008***	0.026***	0.006*	0.001
	(0.006)	(0.004)	(0.018)	(0.003)	(0.003)	(0.006)	(0.003)	(0.016)
Volume *Prosegur* (in logs)	-0.150***	-0.150***	-0.129***	-0.150***	-0.150***	-0.134***	-0.150***	-0.151***
	(0.017)	(0.017)	(0.074)	(0.016)	(0.016)	(0.015)	(0.017)	(0.017)
IGBM (in logs)	1.139***	1.122***	1.034***	1.130***	1.129***	1.068***	1.124***	1.118***
	(0.071)	(0.072)	(0.018)	(0.072)	(0.542)	(0.079)	(0.073)	(0.071)
Constant	-4.279***	-4.174***	-4.360***	-4.243***	-4.210***	-4.080***	-4.181***	-4.138***
	(0.526)	(0.538)	(0.530)	(0.536)	(0.542)	(0.562)	(0.554)	(0.537)
N	518	518	518	518	518	518	518	518
R^2	0.328	0.325	0.421	0.336	0.335	0.357	0.330	0.325
F-stat	101.58	102.11	117.23	105.70	107.86	97.94	99.95	103.18
RMSE	0.252	0.252	0.234	0.250	0.250	0.246	0.251	0.252

Table 7. VAR models and Granger causality tests between the GSVI for the keyword *ocupa* and the GSVI for the keyword *camaras de seguridad*

The table shows the VAR model between the Google Search Volume Index (GSVI) for the keyword *ocupa* and the GSVI for the keyword *camaras de seguridad* in Panel A. The number of lags has been selected according to Akaike´s (AIC) criteria (*p=4)*. Panel B shows the Granger causality Wald tests in which null hypothesis is that the GSVI for a given keyword does not cause the GSVI of the other keyword. Therefore a rejection of the null hypothesis indicates Granger causality. *, ** and *** denote significance at 10%, 5% and at 1%.

Panel A. VAR models		
Dependent variable	GSVI *ocupa*	GSVI *camaras de seguridad*
GSVI $ocupa_{t-1}$	0.465***	0.136*
	(0.043)	(0.070)
GSVI $ocupa_{t-2}$	0.206***	0.163**
	(0.047)	(0.076)
GSVI $ocupa_{t-3}$	0.139***	-0.192**
	(0.047)	(0.076)
GSVI $ocupa_{t-4}$	0.028	-0.025
	(0.044)	(0.071)
GSVI *camaras de seguridad*$_{t-1}$	-0.018	0.264***
	(0.027)	(0.043)
GSVI *camaras de seguridad* $_{t-2}$	0.020	0.205***
	(0.027)	(0.044)
GSVI *camaras de seguridad* $_{t-3}$	-0.025	0.058
	(0.027)	(0.044)
GSVI *camaras de seguridad* $_{t-4}$	0.061**	0.113***
	(0.026)	(0.043)
Constant	0.246**	0.890***
	(0.108)	(0.174)
R-squared	0.596	0.271
AIC		2.146
HQIC		2.201
Number of observations		514
Panel B. Granger causality tests		
GSVI *ocupa* Granger causes GSVI *camaras de seguridad*		15.40***
GSVI *camaras de seguridad* Granger causes GSVI *ocupa*		6.90

Table 8. Placebo test

The table shows the regressions for the placebo analysis. The close price in logs of the IGBM is the dependent variable in Models 1 and 2. In models 3 and 4, it is the close price of IBEX-35 in logs. In models 5 and 6 it is the adjusted close price in logs of Banco Santander (Santander). In Models 7 and 8, it is the adjusted close price in logs of Repsol. GSVI *ocupa* represents the Google Search Volume Index for the keyword *ocupa* in logs. *Dummy COVID-19* is a variable which takes the value 1 during the COVID-19 pandemic (after March 2020) and zero otherwise. *Company volume* represents the volume of stocks negotiated for each of the companies (Santander and Repsol). *, ** and *** denote significance at 10%, 5% and at 1%

	Model 1 IGBM	Model 2 IGBM	Model 3 IBEX-35	Model 4 IBEX-35	Model 5 Santander	Model 6 Santander	Model 7 Repsol	Model 8 Repsol
GSVI *ocupa* (in logs)	-0.051***	0.008	-0.045***	0.010	-0.093***	-0.018	-0.139***	-0.104***
	(0.014)	(0.013)	(0.014)	(0.013)	(0.027)	(0.011)	(0.019)	(0.013)
Dummy COVID-19		-0.282***		-0.262***				
		(0.018)		(0.017)				
Company Volume (in logs)						-0.007		-0.086***
						(0.009)		(0.014)
IBEX-35 (in logs)						1.655***		0.890***
						(0.051)		(0.044)
Constant	6.945***	6.833***	9.224***	9.121***	1.473***	-13.65***	2.669***	-4.013***
	(0.032)	(0.030)	(0.031)	(0.030)	(0.058)	(0.524)	(0.043)	(0.533)
N	518	518	518	518	518	518	518	518
R^2	0.032	0.301	0.027	0.276	0.034	0.817	0.110	0.524
F-stat	12.43	167.46	10.45	152.60	11.77	361.27	49.66	205.95
RMSE	0.141	0.120	0.136	0.117	0.251	0.109	0.200	0.146