

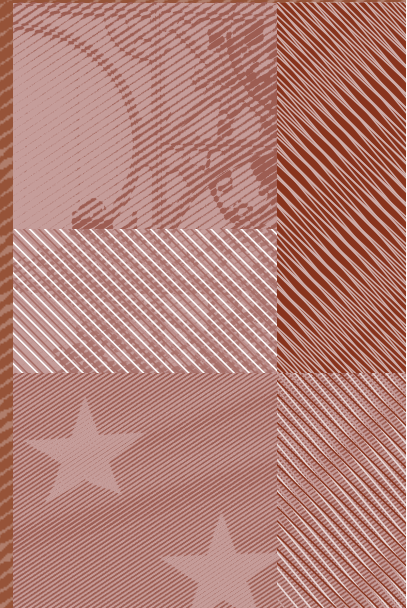
**PRICING DECISIONS UNDER
FINANCIAL FRICTIONS:
EVIDENCE FROM THE WDN SURVEY**

2017

José Manuel Montero

**Documentos de Trabajo
N.º 1724**

BANCO DE ESPAÑA
Eurosistema



**PRICING DECISIONS UNDER FINANCIAL FRICTIONS: EVIDENCE
FROM THE WDN SURVEY**

PRICING DECISIONS UNDER FINANCIAL FRICTIONS: EVIDENCE FROM THE WDN SURVEY ^(*)

José Manuel Montero ^(**)

BANCO DE ESPAÑA AND UNIVERSIDAD COMPLUTENSE DE MADRID

(*) The views expressed in the article are those of the author and do not involve the responsibility of Banco de España or the Eurosystem. I thank Cristina Guillamón for excellent research assistance and Thomas Mathä and Ladislav Wintr for providing data for Luxembourg. Comments from seminar participants in Banco de España, the Simposio de Análisis Económico 2016 (Bilbao) and in the Wage Dynamic Network (Frankfurt) are gratefully acknowledged.

(**) E-mail: jmontero@bde.es.

The Working Paper Series seeks to disseminate original research in economics and finance. All papers have been anonymously refereed. By publishing these papers, the Banco de España aims to contribute to economic analysis and, in particular, to knowledge of the Spanish economy and its international environment.

The opinions and analyses in the Working Paper Series are the responsibility of the authors and, therefore, do not necessarily coincide with those of the Banco de España or the Eurosystem.

The Banco de España disseminates its main reports and most of its publications via the Internet at the following website: <http://www.bde.es>.

Reproduction for educational and non-commercial purposes is permitted provided that the source is acknowledged.

© BANCO DE ESPAÑA, Madrid, 2017

ISSN: 1579-8666 (on line)

Abstract

I test the predictions from Duca, Montero, Riggi and Zizza (2017), who develop a customer-market model with consumer switching costs and capital-market imperfections in which price-cost markups behave countercyclically, with a subsample of European firms participating in the Wage Dynamics Network 2014 survey. I use a novel empirical approach developed by Aakvik, Heckman and Vytlačil (2005) for estimating discrete choice models with binary endogenous regressors that allows for selection on unobservables. Results show that firms subject to financial constraints had a significantly higher probability of raising markups than in a counterfactual scenario without such constraints. Moreover, the estimated partial effects for the main variables are in overall accordance with the predictions from the theoretical model.

Keywords: markups, financial frictions, customer market, discrete-choice models.

JEL classification: C25, C26, D22, L11.

Resumen

En este trabajo se contrastan las predicciones teóricas del modelo elaborado por Duca, Montero, Riggi y Zizza (2017). Este es un modelo de mercados de clientes (*customer markets*) con costes de cambio de proveedor (*switching costs*) e imperfecciones en los mercados de capitales, en el cual los márgenes precio-coste se comportan de manera contracíclica (es decir, aumentan durante las recesiones). Para el análisis empírico se utiliza una submuestra de empresas europeas participantes en la edición de 2014 de la encuesta de la Wage Dynamics Network. Además, se emplea una metodología empírica novedosa desarrollada en Aakvik, Heckman y Vytlačil (2005) que permite la estimación de modelos de elección discreta con variables binarias endógenas y controlar por la posible presencia de sesgos de selección por factores inobservables. Los resultados muestran que las empresas europeas que estuvieron sometidas a restricciones financieras tuvieron una mayor probabilidad de elevar sus márgenes que en un escenario contrafactual sin tales restricciones. Además, en general el efecto estimado de los principales determinantes de la probabilidad de aumentar los márgenes tiende a coincidir con las predicciones del modelo teórico.

Palabras clave: márgenes precio-coste, fricciones financieras, mercados de clientes, modelos de elección discreta.

Códigos JEL: C25, C26, D22, L11.

1 Introduction

The European economy experienced a deep and persistent economic and financial crisis during the period 2010-2013. However, inflation did not fall as much as predicted by standard economic theory, as documented by Gilchrist *et al.* (2016) and Antoun de Almeida (2015). Importantly, this lack of significant disinflation occurred against a backdrop of severe financial shocks that generated substantial economic dislocation throughout the European economies. Gilchrist *et al.* (2016) provide empirical evidence that shows that between 2009 and 2013 inflation in the euro area periphery –those countries most exposed to the financial shocks– was influenced importantly by the severe disruptions in the credit intermediation process. More specifically, they find that the residuals from a Phillips curve-type relationship for a panel of euro area countries are systematically related to several indicators of business credit conditions.

As suggested by Yellen (2016), there are some driving forces of inflation that are not well understood yet, featuring prominently the declining influence of labor market conditions on inflation in recent years. Several recent papers have addressed this puzzling behavior of prices during the crisis paying attention to different dimensions of the inflation process.¹ This paper attempts to contribute to this literature by focusing on the role of financial frictions in firms' pricing decisions, which is the subject of an active ongoing research effort.² To this end, I start from the theoretical model developed by Duca *et al.* (2017), which will guide the empirical analysis and help in interpreting the different mechanisms at work. This is a customer-market model with consumer switching costs and capital-market imperfections very similar to that in Chevalier and Scharfstein (1996). Intuitively, in periods of low demand firms are more likely to be liquidity constrained. In this setting, firms operating in a customer-market framework may find it optimal to increase their prices to boost short run profits and sacrifice future sales, since the possibility of default makes firms care less about the future.

Duca *et al.* (2017) introduce two additional mechanisms that magnify the effects of financial frictions on markup countercyclicality. The first one is the possibility of persistence in demand shocks. This is a relevant feature in view of the exceptional persistence of the shocks affecting the European economy over 2010–2013, as stressed in

¹ See e.g. Coibion and Gorodnichenko (2015) and the references therein.

² See *inter alia* Gilchrist *et al.* (2017) and Duca *et al.* (2017) and the references therein.

e.g. ECB (2014). According to the theoretical model, higher expected persistence tends to augment the effects of financial constraints by strengthening the trade-off between short- and long-run profits. When the negative demand shock is expected to persist in the future, it is less profitable to lower current prices to increase market share and future profits.

The second extension, which also reinforces that trade-off, consists in allowing a procyclical elasticity of demand, so that firms perceive stronger competition in expansions than during downturns, a point that dates back to Robinson (1933). As the elasticity of demand falls in a downturn, firms become *insulated* from competition because the gain from a given price cut becomes smaller, which reduces the benefit from investing in market shares and, thus, long-run profits. Arguably, this is also a relevant feature of the European economy that should be taken into account, as the degree of competition might have decreased over the crisis as a result of an increase in the rate of business destruction which would have bolstered surviving firms' market power.

In this paper, I study these predictions with a subsample of European firms participating in the third wave of the Wage Dynamics Network (WDN) survey carried out in 2014 by the European System of Central Banks (ESCB), covering firms from 25 ESCB countries and from a wide range of sectors. The survey consists almost exclusively of qualitative questions and is particularly suitable for the purpose of this paper, as companies are asked directly how they changed their price-cost margins over the period 2010-2013, together with questions related to the evolution of perceived competition, of demand for their products and to the difficulties in obtaining external financing through the usual financial channels. Further, I use a novel empirical approach developed by Aakvik, Heckman and Vytlačil (2005) for estimating discrete choice models with binary endogenous regressors that allows to control for selection on unobservables.

The empirical results in this paper reveal that firms subject to financial constraints had a significantly higher probability of raising markups than in a counterfactual scenario without such constraints, in particular, for those in the manufacturing sector. Moreover, the estimated partial effects for the main variables of interest according to the model show that over the period 2010-2013 the likelihood of increasing markups was procyclical on average, but it was less procyclical when competitive pressures fell during the downturn and when the shock to demand was expected to persist. Indeed, if we take the average partial effects at face value, the negative effect of an adverse demand shock on the likelihood of raising markups would be much higher on average in those cases when the fall in demand did not come together with a fall in competition and an increase in

persistence. All in all, the empirical results are consistent with those found in the previous literature and are mostly in accordance with the predictions from the theoretical framework.

The paper is organized as follows. Section 2 relates this work to the previous literature. Section 3 briefly lays out the theoretical framework and explains the empirical strategy. Section 4 describes the dataset, while Section 5 discusses the results and Section 6 concludes.

2 Related literature

There is a growing literature that assesses both the empirical and theoretical relevance of financial constraints for price and markup determination. The idea that firms set prices taking into account the trade-off between current and expected future demand and that this decision may be affected by imperfections in capital markets was first introduced by Gottfries (1991) and Chevalier and Scharfstein (1996). As emphasized in these two contributions, firms operating in customer markets may find it optimal to increase their prices to boost short run profits and sacrifice future sales, when they face a fall in demand accompanied by a liquidity shortage. Some early empirical evidence of this hypothesis was provided by Chevalier and Scharfstein (1996) for the US supermarket industry in the late 1980s and early 1990s. More recent empirical support was presented by Asplund *et al.* (2005) for the case of the Swedish newspaper industry during the deep recession starting in 1990; or by Kimura (2013) for the post-bubble Japanese economy of the 1990s, where deflationary forces were attenuated despite large fluctuations in the real economy, in part due to the impact of deteriorating financial conditions on firms' pricing decisions.

The debate on the role of financial frictions in corporate pricing policies gained prominence during the Great Recession, as the extraordinary turmoil that swept through financial markets during this period was accompanied by only a mild decrease in inflation in most advanced economies. One of the first contributions was Montero and Urtasun (2014) for the case of Spain, an economy particularly affected by financial turbulence. Using a panel of firm-level data, they find a significant increase in estimated Spanish firms' price-cost markups since 2007. Besides, they show that this finding is related to the high degree of financial pressure faced by Spanish firms over the crisis period, on the background of an increase in the pace of business destruction which probably resulted in

a strengthening of surviving firms' market power that also tended to increase average markups.

Gilchrist *et al.* (2017) was also an early and relevant contribution. They use a micro-level data set containing good-level prices underlying the construction of the US PPI merged with the respondent firms' balance sheets to analyze how differences in firms' internal liquidity positions affect their price-setting behavior during the recent financial crisis. They find that liquidity unconstrained firms slashed prices in 2008, whereas those with limited internal liquidity significantly increased their prices. Further, they develop a general equilibrium model in which monopolistically competitive firms face costly price adjustment and costly external finance, while setting prices to actively manage current versus future demand. Model simulations show that in response to an adverse financial shock, firms with limited internal resources raise prices relative to their financially stronger competitors, consistently with the previous empirical evidence.

Gilchrist and Zakrajsek (2015) provide additional evidence for the US economy by using data at the industry level for a long time span. They find that prices in industries in which firms rely more heavily on external finance, thus facing a higher likelihood of financing constraints, declined noticeably less in response to economic downturns associated with a significant tightening of financial conditions. Moreover, they dig further into the implications of the Gilchrist *et al.* (2017)'s theoretical model by exploring the macroeconomic implication of different interest-rate policy rules.

Antoun de Almeida (2015) and Gilchrist *et al.* (2016) provide evidence for a systematic effect of financial constraints on industry-level producer prices in the euro area.³ In the former case, she shows that there is a negative and significant relationship between sectoral inflation and firms' liquidity conditions only for euro area countries under distress. A similar result is documented in the latter paper. They find that changes in business credit conditions during the crisis are systematically related to the inflation residuals from canonical Phillips curve-type relationships only for periphery euro area countries.⁴

³ Balleer *et al.* (2015) study how financial market imperfections interact with the frequency of price adjustment and, using firm-level data, document that financially constrained German firms were more likely to increase prices than their unconstrained counterparts over 2002-2014.

⁴ They also construct a dynamic multi-country general equilibrium model building on Gilchrist *et al.* (2017) to analyze the business cycle and welfare consequences of forming a monetary union among countries with different degrees of financial market distortions.

Duca *et al.* (2017) build on the customer-market model with capital market imperfections developed by Chevalier and Scharfstein (1996) to extend it in two directions: they allow for persistence in demand shocks and assume a procyclical elasticity of demand. It is shown that these two additional mechanisms magnify the effects of financial frictions on the degree of markup countercyclicality (as I will explain below). They use firm-level data from the 2014 Wage Dynamics Network Survey for Italian firms and find that financially constrained firms had a higher likelihood of increasing their price-cost markups when faced with a declining demand; and this result is strengthened when the shock to demand is perceived to be persistent. These findings suggest that the severity of the financial turbulence experienced by Italy in 2010-2013 was one of the causes of the sustained rise in prices over this period, despite the significant slack in the economy.

3 Empirical approach

Theoretical framework

In order to rationalize the mechanisms underlying firms' pricing and markup decisions, I will use the theoretical model developed by Duca *et al.* (2017; DMRZ hereafter), which is in turn based on Chevalier and Scharfstein (1996). In a nutshell, it is a spatial competition model with consumer switching costs extended with capital market imperfections à la Hart and Moore (1998). As a novelty, DMRZ introduce the increasing-return shopping technology of Warner and Barsky (1995) to allow the elasticity of demand to be procyclical, which means that firms perceive stronger competition in expansions than during recessions. Moreover, they also assume that firms attribute a certain probability to the event that the first-period state of demand will persist in the future. The theoretical model is fully spelled out in Annex A.

In that setting, firms operate in a customer-markets framework and have a degree of market power over their repeat-purchasers due to the existence of consumer switching costs. Thus, firms' current market shares are valuable, as they determine firms' future profits. In any period, there is a trade-off between investing in market share by setting a low price or extracting rents by setting a high price on their locked-in shoppers. In the scenario when firms are not subject to financial frictions, markups can be either procyclical or countercyclical, depending on the parameters of the model. Markups might decrease in recessions when the fall in current demand relative to future demand makes it more appealing to invest in market shares by cutting prices and increase monopoly

profits in the future, when demand will be relatively high. However, the two additional channels would attenuate the fall in markups. When the low state of demand is expected to persist in the future, the relative convenience of lowering current markups to reap profits in the future, rather than in the present, is weaker. Moreover, when the elasticity of demand decreases very much in a slump, the gain in demand from a given price cut is diminished, thus reducing the benefits from investing in market shares. Table 1 summarizes the main predictions from the theoretical model.

On the other hand, when firms are financially constrained, price markups always behave in a countercyclical fashion. Intuitively, firms are more likely to be liquidity-constrained in recessions, in which case they prefer extracting rents in the short-run by setting a higher price, rather than building market shares to enhance future profits. In addition, this behavior is strengthened when the firm expects the downturn to persist in the future, as the relative appeal of cutting markups to reap profits in the longer-term is diminished. And it is further reinforced the more the elasticity of demand falls in slumps, as firms become more insulated from competition.

Econometric methodology

The theoretical model distinguishes between two types of firms: those subject to financial frictions/constraints (i.e. being exposed to a “treatment”, $fc = 1$), and those internally financed or not subject to financial constraints (i.e. firms in a “control” group, $fc = 0$). Table 1 collects a summary of the main theoretical implications for both types of firms ($j = 0, 1$) in terms of the level of markups (m_j), the cyclical response of markups ($\lambda_j = \partial m_j / \partial demand$), and the sensitivity of this cyclical response with respect to the cyclical elasticity of demand ($\partial \lambda_j / \partial v$), and with respect to the persistence of demand shocks ($\partial \lambda_j / \partial \alpha$).

In other words, as it can be seen in Table 1, the level (m), the cyclical response (λ) and the sensitivity of this cyclical response of a firm’s markup to different economic factors ($\partial \lambda_j / \partial \varphi, \varphi = \{v, \alpha\}$) depend on the regime/state the firm is facing, which in turn is determined by the degree of financial frictions. This setting fits very well with the empirical approach developed by Aakvik *et al.* (2005), who build up a discrete choice model that allows for selection in both observables and unobservables, and it also admits the responses to vary across states.

So let us interpret that “nature” assigns treatment fc_i to each firm i according to the following decision rule:

$$\begin{aligned} fc_i &= 1 \text{ if } fc_i^* = \gamma Z_i - U_{fc,i} \geq 0 \\ fc_i &= 0 \text{ if } fc_i^* = \gamma Z_i - U_{fc,i} < 0 \end{aligned} \quad (1)$$

where Z_i is a vector of observed (by the econometrician) random variables and U_{fc_i} is an unobserved (by the econometrician) random variable; fc_i^* is the net utility that “nature” derives from assigning state 1 (i.e. experiencing financial constraints) to firm i . For each firm i , I assume two potential outcomes m_{0i} and m_{1i} (whether a firm decides to raise its markups or not) corresponding, respectively, to the potential outcomes in the untreated and treated states. Then in this model it is assumed that a linear latent index model (with unobservables generated by a normal factor) generates the outcomes:

$$\begin{aligned} m_{1i} &= I(m_{1i}^* = \beta_1 x_i - U_{1,i} \geq 0) \\ m_{0i} &= I(m_{0i}^* = \beta_0 x_i - U_{0,i} \geq 0) \end{aligned} \quad (2)$$

where $I(\cdot)$ is the usual indicator function. It is worth noting that, in accordance with the theoretical model, I allow the response of markups to differ across regimes (i.e. $\beta_1 \neq \beta_0$). Further, m_{0i} and m_{1i} are not observed simultaneously, but instead:

$$\begin{aligned} m_i &= m_{0i} \text{ if } fc_i = 0 \\ m_i &= m_{1i} \text{ if } fc_i = 1 \end{aligned} \quad (3)$$

I assume that the error terms are driven by the following factor structure:

$$\begin{aligned} U_{fc_i} &= -\theta_i + \varepsilon_{fc_i} \\ U_{1i} &= -\alpha_1 \theta_i + \varepsilon_{1i} \\ U_{0i} &= -\alpha_0 \theta_i + \varepsilon_{0i} \end{aligned} \quad (4)$$

where θ_i , ε_{fc_i} , ε_{0i} and ε_{1i} are jointly distributed $N(0, I)$, and where I is the identity matrix and I have imposed the normalization that $\text{Var}(\theta_i) = \text{Var}(\varepsilon_j) = 1$ for $j = fc, 0, 1$. These assumptions imply that I can identify the correlations between the unobservables related to the selection equation and the unobservables for the outcome equations. These

correlations convey interesting information regarding the relevance of selection on unobservables, and can be computed as:

$$\text{Corr}(U_{fc}, U_0) = \rho_0 = \frac{\alpha_0}{\sqrt{2}\sqrt{1 + \alpha_0^2}}$$

$$\text{Corr}(U_{fc}, U_1) = \rho_1 = \frac{\alpha_1}{\sqrt{2}\sqrt{1 + \alpha_1^2}}$$

Given joint normality, this set of assumptions implies that the joint distribution of the vector (U_{fc}, U_0, U_1) is known.⁵ It is worth noting that in this framework selection on unobservables related to the equation for financial constraints are controlled for through the component θ_i .

The log-likelihood function for this model is:

$$\begin{aligned} \ln(L) = & \sum_{fc_i \neq 0, m_i \neq 0} \ln\{\Phi_2(\beta_1 x_i, \gamma Z_i, \rho_1)\} + \sum_{fc_i \neq 0, m_i = 0} \ln\{\Phi_2(-\beta_1 x_i, \gamma Z_i, -\rho_1)\} \\ & + \sum_{fc_i = 0, m_i \neq 0} \ln\{\Phi_2(\beta_0 x_i, -\gamma Z_i, -\rho_0)\} + \sum_{fc_i = 0, m_i = 0} \ln\{\Phi_2(-\beta_0 x_i, -\gamma Z_i, \rho_0)\} \end{aligned}$$

where $\Phi_2(\cdot)$ is the cumulative distribution function of a bivariate normal distribution.⁶

An important advantage of this latent variable model is that it can be used to estimate mean treatment parameters from a common set of structural parameters, as demonstrated by Aakvik *et al.* (2005). Let's define the treatment effect for a given firm i as $D_i = m_{1i} - m_{0i}$, which is a counterfactual (both outcomes cannot be observed at the same time). In this context, I'm mostly interested in the effect of treatment on the treated (TT), which would give the average effect on the probability of raising markups for a firm subject to "treatment" (i.e. financial constraints). For firms with observed characteristics x it is defined as:

$$\begin{aligned} TT(x_i) & \equiv E(D_i/X = x_i, fc_i = 1) = \Pr(m_{1i} = 1/X = x_i, fc_i = 1) - \Pr(m_{0i} = 1/X = x_i, fc_i = 1) \\ & = \frac{\Phi_2(\beta_1 x_i, \gamma Z_i, \rho_1) - \Phi_2(\beta_0 x_i, \gamma Z_i, \rho_0)}{\Phi_{U_{fc}}(\gamma Z_i)} \end{aligned} \tag{5}$$

⁵ To fully characterize the distribution, it is also needed the correlation $\text{Corr}(U_1, U_0) = \rho_{01} = \frac{\alpha_0 \alpha_1}{\sqrt{1 + \alpha_0^2} \sqrt{1 + \alpha_1^2}}$.

⁶ The vector Z_i may collect a set of instrumental variables, which are not strictly necessary, but help in identifying the model, as argued by Aakvik *et al.* (2005).

One can also be interested in computing some averages of the distribution of $TT(x)$ over the support of X , such as the average treatment effects (ATT) for the corresponding subgroups of the population. This can be easily calculated by averaging the expression for $TT(x)$ over the observations in the subgroups. For instance, the ATT for the whole subsample of “treated” (i.e. financially constrained) firms (N_{fc}) can be calculated as:

$$ATT = \frac{1}{N_{fc}} \sum_{i=1}^{N_{fc}} TT(x_i) \quad (6)$$

A similar expression can be used to calculate the ATT for firms in a given country or with any other characteristic, as it will be shown below.

In short, this is a binary choice model with binary endogenous regressors which is a bit more sophisticated than the bivariate probit or the probit model with sample selection, as both *biprobit* and *heckprobit* assume equality of coefficients in the outcome equations for both treatment regimes.⁷

4 Data

The empirical analysis is based on a unique cross-country dataset on European firms’ employment adjustment strategies, as well as price- and wage-setting behavior, collected through an ad-hoc survey by the European System of Central Banks in 2014 in the context of the third wave of the Wage Dynamics Network (WDN). The questionnaire consists almost exclusively of qualitative questions and includes three types of queries: (i) core harmonized questions, uniformly administered throughout the different countries to allow for international comparison; (ii) non-core questions (also harmonized across countries, but optional); and (iii) local questions, administered only at the country level.⁸

The estimation sample is determined by the availability of the non-core question (NC2.7b) on the evolution of prices vis-à-vis total costs over 2010-2013. Only 7 (out of 25) countries responded to this question on price-cost margins, namely, the Czech Republic, Italy, Latvia, Luxembourg, Malta, Poland and Spain. Moreover, I cleaned observations from regulated and non-market sectors, where pricing decisions are not very much driven by market forces —such as electricity, gas and water, financial intermediation, public sector

⁷ I use the Stata’s command *switch_probit* developed by Lokshin and Sajaia (2011) to estimate this model.

⁸ See http://www.ecb.europa.eu/pub/economic-research/research-networks/html/researcher_wdn.en.html for more details about the database.

services and arts—. ⁹ Firms with less than 5 employees were also dropped, as they were all concentrated on Poland and Luxembourg. The distribution of firms across countries/size strata and industries is given in Table 2.

The dependent variable for the outcome equations (2) in the estimation exercises is a dummy variable coded as unity if the firm raised markups, and zero otherwise. To be more specific, it equals one when firms replied that prices (as compared to total costs) increased either moderately or strongly during 2010–2013. ¹⁰

Secondly, I include information on the main variables of interest according to the theoretical model described in Section 3. These variables are the dynamics of demand, the evolution of perceived competition –as an approximation for the evolution of the elasticity of demand–, the persistence of demand shocks, and the extent of financial constraints. I account for the dynamics of demand (i.e. the proxy for the cycle or the state of demand) by introducing a dummy which is equal to one if the firm reported a negative evolution (strong/moderate decrease) of the domestic or foreign demand for its main product/service during 2010-2013. Regarding the degree of perceived competition, I define a dummy which equals one when firms report a (strong/moderate) decrease in competitive pressure on its main product/service (either on domestic or foreign markets), compared to the situation before 2008. Additionally, I will proxy for the level of demand persistence through firms' perception about volatility/uncertainty of their demand. A higher volatility is interpreted as meaning that shocks are expected to be less persistent, as the likelihood that there will be a future reversal of demand is higher. Thus, the dummy for the volatility of demand for the firm's main product is coded as one when the firm reports that volatility has not had a negative effect on its activity during 2010-2013, because high volatility is likely to be perceived as a negative factor. ¹¹

⁹ As argued in DMRZ, the theoretical model is based on the presumption that consumers develop switching costs after their initial purchases, which provides firms with a certain degree of market power over their customer base. Thus, in the empirical exercise it would be desirable to restrict the sample to firms in industries which are more prone to develop this type of “brand loyalty”. A priori, as argued by Motta (2004, pp 79-81) and Klemperer (1995), one can realistically think that the existence of switching costs is a widespread phenomenon across many industries. For this reason, I prefer to do a minimal cleaning and only drop firms belonging to regulated and non-market sectors. Additionally, Gilchrist *et al.* (2017) provide several references in support of the fact that customer markets are an important feature of the major sectors in the US economy.

¹⁰ The remaining categories are strong decrease, moderate decrease or unchanged.

¹¹ In the experience of the WDN, firms tend to reply to the question about how the volatility of demand affected their activity having in mind that high volatility is a negative factor. Moreover, in the WDN survey about two thirds of firms reporting that volatility/uncertainty had a strong negative effect on their activity

Additionally, and more importantly, I consider variables accounting for credit availability in order to define the dependent variable for the selection equation (1). In particular, the survey asked firms to relate the difficulties in obtaining credit to the main purpose for which finance was needed. Namely, they were asked to assign a ranking (“not relevant”, “of little relevance”, “relevant”, “very relevant”) to the events “Credit was not available” and “Credit was available but conditions were too onerous” for financing the following activities: (i) working capital, (ii) new investment, and (iii) refinance existing debt (rollover). Firms were defined as financially constrained (dummy *fc* equal to one) if they replied “relevant” or “very relevant” to any of the six questions.¹²

Finally, I also account for several firm-level characteristics (all of them 0/1 dummies) which are potentially relevant for the price-markup decision and as determinants of financial constraints. These variables are the country of origin, sectoral dummies (industry, trade and business services), firm size (three dummies: for less than 50, between 50 and 199 and at least 200 employees), nationality of the ownership (mainly domestic or mainly foreign), degree of autonomy (namely, whether the firm is a subsidiary/affiliate or not) and organizational structure (single- or multi-establishment firm).

Table 3 contains descriptive statistics of the variables used in the empirical analysis for treatment vs non-treatment status. There exist clear differences in the observable characteristics between treated and non-treated firms that, besides, are mostly statistically significant. The treated units are more likely to be small and medium-sized (5 pp on average), younger (one year on average), and more likely to operate in the manufacturing-construction sector.¹³ Moreover, the share of firms that are foreign-owned, a subsidiary or part of a multi-establishment firm is lower among financially-constrained firms. Furthermore, these firms are more likely to report a fall in demand and a fall in the degree of competition, while they are less probable to have a lower volatility. Finally, although there is a slightly higher (unconditional) likelihood of raising their price-cost margins (more on this below) for non-financially constrained businesses (27% vs 26%), it is not statistically significant.

considered this effect transitory or at worst partly persistent (see Annex B for the wording of the question). This would support the view that negative shocks that are volatile are more likely to be less persistent.

¹² I also tried with a less stringent definition whereby a firm is considered as financially-constrained when it replies “relevant” or “very relevant” to at least one of the questions in the block “Credit was not available” and at least one in the part “Credit was available but conditions were too onerous”. Results were very similar.

¹³ In this case, the difference is not statistically significant at conventional levels.

5 Results

Let me start with a brief discussion of the estimated coefficient values from the selection and the outcome equations. Then, I report estimates of the mean treatment parameters (for the population of WDN firms) derived from those estimated coefficients, as well as the partial effects for the main regressors of interest. As noted above, under the normality and factor structure assumptions no exclusion restrictions are required to identify the mean treatment effects. However, as recommended by Aakvik *et al.* (2005), I use a (plausible) exclusion restriction to enhance identification: firm's age, which besides being an important determinant of the probability of being subject to financial constraints,¹⁴ it complies with the fundamental requirement that is available for all the 7 countries. I thus follow DMRZ who also use firms' age as an instrument in a similar context. The literature has shown that a firm's age is a particularly useful predictor of financial constraint levels.¹⁵ Moreover, an appealing feature of this variable is that it is much less endogenous than most other usual proxies for financial constraints, such as a firm's leverage and cash flow. In short, it is reasonable to expect a firm's age to influence its probability of being financially constrained, but not to affect the markup decision directly —only through its impact on financial constraints—. Indeed, estimation results reported in Table 8 below support the choice of age as a reasonable instrumental variable.

Estimated coefficients and mean treatment parameters

Table 4 reports estimation results for the selection equation and the two outcome equations. Starting with the selection equation, consistent with figures in Table 3, there is a clear evidence that there is non-random selection into “treatment”, i.e. firms subject to financial constraints differ significantly from those not subject to such constraints with respect to observable characteristics. For instance, those characteristics attached to a lower probability of suffering financial problems are: experiencing a fall in volatility, or being a subsidiary or a foreign-owned company. The coefficient on our instrumental variable (age) has the expected negative sign and is statistically significant.

¹⁴ The rationale is that information asymmetries are likely to be especially large for newly-established firms, because creditors have not had enough time to monitor such firms and because such firms have not had enough time to build long-term relationships with suppliers of finance (see *inter alia* Coluzzi *et al.*, 2015, and references therein).

¹⁵ Hadlock and Pierce (2010) find that financial constraints fall sharply as young (and small) firms start to mature and grow. Eventually, these relations appear to level off.

Regarding regression results for the outcome equations (columns 2 and 3), those firms suffering a negative demand shock have lower chances of raising markups over the period 2010-2013, with a similar coefficient in both states. This effect is dampened if the demand shock comes together with a fall in competition. Other statistically significant coefficients are those for a fall in competition (with a negative sign), being a subsidiary (with opposite sign across states) and being a foreign-owned firm for $fc = 0$.

Another important piece of information comes from the correlation among unobserved components. The estimated correlation ρ_0 suggests that the unobservables that promote financial constraints are highly negatively correlated with the unobservables that promote higher markups in the no-financial-constraints state. However, those unobservables are highly positively correlated with the unobservables that promote higher markups in the financially constrained state (positive ρ_1). Thus, firms which are more likely to suffer financial constraints (i.e. with low values of U_{fc}) are more likely to have higher treatment effects; hence, selection is positive for the outcome. Finally, the LR test strongly rejects the null hypothesis of no selection bias due to unobservables (i.e. H_0 : error terms are independent across equations) at conventional levels.

Additionally, one interesting issue that can be studied with this empirical framework is whether firms experiencing a financial shock have a larger likelihood of raising markups than firms non-financially constrained. In order to do this, one can use expressions (5)–(6) above for computing the different mean treatment parameters associated with the estimated parameters just reported. I find (see the final rows of Table 4) that the $ATT = E(D|fc = 1) = 0.237$, which suggests that a firm subject to financial constraints had a 23.7 pp higher probability of raising markups compared with the counterfactual scenario of firms operating without financial constraints.¹⁶ Using the vocabulary from the program evaluation literature, these results suggest that selection into treatment (suffering a financial shock) was highly positive for the outcome (increasing markups), which is consistent with the estimated correlation coefficients described in the previous paragraph. In comparison, as reported in Table 3, the raw difference in mean outcomes is -0.011 (i.e. $E(m_1|fc = 1) - E(m_0|fc = 0) = -0.011$). Thus, controlling for selection (both on observables and on unobservables) appears to have a substantial impact on the point estimates for mean treatment effects.

¹⁶ Bootstrapped standard errors for ATT are very large, which might be suggesting that much larger sample sizes are needed to accurately estimate this type of model.

It is also interesting to study the degree of heterogeneity in the distribution of treatment effects by a firm's country of origin. Table 5 reports some descriptive statistics for the distribution of TT by country. It reveals that the ATT is larger for firms from Eastern European countries (CZ, PL, LV). The ATT is lower for Italian firms, while that for Spanish firms would be in a middle position. Figure 1 displays the kernel densities of these treatment effects grouping together firms for each one of the three largest economies (ES, IT and PL) and for the rest. It is worth noting that the estimated treatment effects are always positive, and that the distribution for Spanish firms is shifted to the right of the distribution for Italian firms, while that for Polish corporations is further shifted to the right. Thus, these results suggest that firms subject to financial constraints in Spain or in Poland had a higher probability of raising markups than in Italy, as compared to a counterfactual scenario without financial constraints.

Estimated partial effects of main variables

I can go a step further and compute the partial effects of the main variables on the probability of increasing price-cost margins in both states ($fc = 0$ and $fc = 1$) and check whether these effects are consistent with the predictions from the theoretical model. To be more specific, and for simplicity, assume that the empirical model can be written as:

$$E(m|x_1, x_2, z, fc) = F(\beta_1x_1 + \beta_2x_2 + \beta_{12}x_1x_2 + \delta z)$$

where I have omitted subscripts and $m = 1$ if the firm raises markups (0 otherwise); x_1 stands for the variable "fall in demand" and $x_2 = \{\text{"fall in competition", "fall in volatility"}\}$. In order to test the predictions of the theoretical model, I want to estimate, first, the partial effects associated with the cyclical variable (fall in demand, i.e. x_1). In other words, the following expression provides how much the probability of increasing markups changes when the state of demand goes from a boom to a downturn:

$$\frac{\Delta E(m|x_1, x_2, z, fc)}{\Delta x_1} = F(\beta_1 + \beta_2x_2 + \beta_{12}x_2 + \delta z) - F(\beta_2x_2 + \delta z)$$

And second, according to the theoretical framework, this partial effect changes when the degree of either competition or persistence changes. Therefore, one would like to calculate the following cross “derivative”:¹⁷

$$\Delta(x_1, x_2) = \frac{\Delta^2 E(m|x_1, x_2, z, fc)}{\Delta x_1 \Delta x_2}$$

Ai and Norton (2003) and Greene (2010) show that this expression is as follows:

$$\Delta(x_1, x_2) = [F(\beta_1 + \beta_2 + \beta_{12} + \delta z) - F(\beta_2 + \delta z)] - [F(\beta_1 + \delta z) - F(\delta z)]$$

Then asymptotic standard errors for the partial and interaction effects can be calculated using the delta method. It is worth noting that with this approach I can compute a partial effect and its associated standard error for each observation, i.e. it is obtained a distribution of partial effects for the whole sample of firms (Greene, 2010). Consequently, since it is difficult to create a single number that summarizes all the partial effects, in Table 6 I report the estimated average partial effects (APE) across all observations, as well as the max/min effects and the max/min Wald statistics for the test of significance of individual partial effects. Further, I also report the share of partial effects that are statistically significant (below each APE) to give a flavor of overall statistical significance.

As shown in Table 6, the likelihood of increasing markups is procyclical on average, in the sense that the partial effect for “fall in demand” is negative. And this is the case for both financially and non-financially constrained firms, which in the former instance would be inconsistent with the theoretical model. The APE is around -0.18 in both cases, a large magnitude: changing from an increase to a decrease in demand lowers the probability of increasing markups by 18 percentage points. Moreover, the range of estimated partial effects and the degree of statistical significance is somewhat similar across both types of firms. Figure 2 displays the distribution of partial effects by country, with special focus on Spain. It is interesting to note that while all the partial effects are negative, those for Spanish firms are relatively shifted to the right. In other words, the likelihood of higher markups is less procyclical in this country. Further, the partial effects for “fall in demand” are less negative (i.e. the probability of raising markups is less procyclical) when competitive pressures fall during the downturn on average, which is consistent with the

¹⁷ Strictly speaking we cannot speak about derivatives, but rather about discrete differences, as we are dealing with binary variables.

model's predictions. However, I find a lower degree of statistical significance (with an average around 30%) for these partial effects than for the previous ones (average around 90%). Finally, that partial effect would also be less negative (markups would be less procyclical) in both states the more the shock to demand is expected to persist (i.e. when volatility falls), although the estimated interaction effects are not statistically significant across the whole distribution of firms. All in all, if one takes the three APE at face value, the negative effect of an adverse demand shock on the likelihood of increasing markups would be much higher on average in those cases when the fall in demand does not go hand in hand with a combined fall in competition and increase in the persistence of the shock.

Robustness

Table 7 reports the estimated partial effects and mean treatment parameters for a set of alternative specifications. In the first two set of estimates (Panel A) I introduce an additional dimension of heterogeneity by considering separately the baseline scenario for firms in the manufacturing sector and in the services sector.¹⁸ Although the overall message is similar, it is worth remarking the higher degree of statistical significance in the results for manufacturing firms, which would suggest that the customer-market model with financial constraints fits better this type of firms. Moreover, the ATT is large and statistically significant, while the interaction of a fall in demand and in volatility has a positive and significant effect for (almost) all manufacturing firms. Indeed, in this case, a combined scenario of a negative shock in demand with a fall in the degree of competition and an increase in the degree of persistence would deliver a substantially smaller procyclical likelihood of raising markups, consistently with our theoretical model. Results for firms in the services sector are in line with the baseline, although with a lower degree of statistical significance. Figure 3 shows the distribution of treatment effects by country. The kernel densities are very similar to those in Figure 1, with the distribution for Spanish firms in between the distribution for Italian and Polish firms. The distribution for manufacturing firms seems to be somewhat more spread than for services firms.

Removing sampling weights (Panel B, first columns) from the estimation does not alter our results, while replacing sampling with employment weights (Panel B, latter columns) yields similar results as well. In both cases, we find a lower degree of statistical

¹⁸ There are some fundamental differences between manufacturing and services firms that would justify considering them separately, such as the tangibility of their products, the possibility of holding inventories, or the requirement of a physical production site.

significance in the partial effects for the interaction between a fall in demand and a fall in competition. And lastly, as there is not much evidence about financial frictions and pricing behavior by firm size, in Panel C I report estimation results when heterogeneity by firm size is considered. The model is estimated for firms split into two groups: small-sized (those with up to 50 employees) and medium- and large-sized firms (over 50 employees). As I have argued above, smaller firms are more financially fragile, so one would expect them to be more responsive when faced with a financial shock. However, I find that estimated partial effects are quite similar across both types of firms (and with respect to the baseline specification). Regarding the ATT, it is also similar, even slightly bigger for larger firms.

In Table 8 I compare the baseline estimated treatment parameters and partial effects with the estimates produced from some alternative linear estimators to assess whether the results are mainly driven by the highly nonlinear approach I follow. In particular, I use the linear IV approach suggested by Angrist (2001) or Angrist and Pischke (2009). Thus, I first impose a linear probability model for the outcome equation assuming that treatment (i.e. $fc = 0, 1$) only shifts its intercept, and use the variable age as instrumental variable in a 2SLS regression. This approach has the additional benefit that it allows to check the strength of the instrumental variable used. Results in the first column of Table 8 indeed show that the estimates based on linear 2SLS are very close to those from the Aakvik *et al.* (2005) approach, which is reassuring. The ATT is 0.207, close to the baseline 0.237, while the coefficients for the main variables of interest have the same sign than in the baseline specification. The APE for a fall in demand is -0.148, again near -0.18 in the baseline.¹⁹ Moreover, I also report at the bottom of the first column some statistics to assess the quality of the instrumental variable. Firm's age is highly significant in the first stage regression, and even though the F statistic is slightly below 10, the Wald statistic for the Cragg-Donald test of weak instruments would pass the test for a 15% rejection rate (test size). Thus, firm's age seems to be a reasonably good instrumental variable. Finally, when I split the sample in two (between firms with $fc = 0$ and those with $fc = 1$) and estimate a simple linear probability model by OLS, I also obtain similar results in terms of the signs of the coefficients for the main variables of interest.

¹⁹ The APE is computed evaluating the expression $-0.284 + 0.294 \cdot fall_in_compet_i + 0.183 \cdot fall_in_volat_i$ at the mean of the variables considered.

6 Conclusions

In this paper I have used the third wave of the WDN survey to investigate the role of financial frictions in firms' price-setting behavior in some European economies over the crisis period between 2010 and 2013.

In order to rationalize the empirical results, I start from the customer-market model with financial frictions developed in Duca *et al.* (2017). In this setting, price markups behave in a countercyclical fashion if firms are financially constrained, as they are more likely to be liquidity-constrained in recessions and, thus, place a greater weight on short-run profits than on future profits. This behavior is further strengthened when the state of demand is perceived to be highly persistent and the more the competitive pressures fall during busts, as it diminishes the convenience of lowering current markups to reap future profits.

I take this model to the data using a subsample of European firms participating in the 2014 version of the WDN survey. Moreover, given the characteristics of the database, which consists mostly of qualitative variables, I use a novel empirical approach developed in the context of the treatment effects literature by Aakvik *et al.* (2005) for estimating discrete choice models with binary endogenous regressors and unobservables generated by factor structures. I find that firms subject to financial constraints had a significantly higher probability of raising markups than in a counterfactual scenario without such constraints. This treatment effect is statistically significant for manufacturing firms. Moreover, the estimated partial effects for the main variables of interest in the model show that the likelihood of increasing markups decreases when demand falls, but less so when competitive pressures fall during downturns and when the shock to demand is expected to persist. If one takes the average partial effects at face value, the negative effect of an adverse demand shock on the likelihood of raising markups would be much higher on average in those cases when the fall in demand does not come together with a combined fall in competition and an increase in persistence. All in all, the empirical results are mostly in accordance with the predictions from the theoretical framework, the main exception being the finding that the probability of increasing price margins seems to be procyclical for financially-constrained firms.

In sum, these findings suggest that the extreme degree of financial turbulence experienced by the European economy over the period 2010-2013 could be a relevant factor behind the dampened evolution of inflation in many countries. This would also be consistent with the available results obtained recently for Japan, the US, Spain or Italy.

Thus, the evidence presented in this paper supports the view that any attempt to understand price-cost margins in the aggregate must account for firms' differential access to capital markets over time. The interaction between a firm's balance sheet position and its pricing decision is an interesting avenue for future research.

References

- [1] Aakvik, A., J. J. Heckman, and E. J. Vytlacil (2005): "Estimating Treatment Effects for Discrete Outcomes When Responses to Treatment Vary: An Application to Norwegian Vocational Rehabilitation Programs", *Journal of Econometrics*, 125, 15-51.
- [2] Ai, C. and E. C. Norton (2003): "Interaction Terms in Logit and Probit Models", *Economics Letters*, 80, 123-129.
- [3] Angrist, J. D. (2001): "Estimation of Limited Dependent Variable Models with Dummy-Endogenous Regressors: Simple Strategies for Empirical Practice", *Journal of Business & Economic Statistics*, 19, 2-16.
- [4] Angrist, J. D. and J.-S. Pischke (2009): "Mostly Harmless Econometrics: An Empiricist's Companion", Princeton University Press.
- [5] Antoun de Almeida, L. (2015): "Firms' Balance Sheets and Sectoral Inflation in the Euro Area during the Financial Crisis", *Economics Letter*, Vol. 135, pp 31-33.
- [6] Asplund, M., R. Eriksson and N. Strand (2005): "Prices, Margins and Liquidity Constraints: Swedish Newspapers 1990-1996", *Economica*, 72(286), 349-359.
- [7] Balleer, A., N. Hristov, M. Kleeman and D. Menno (2015): "Financial Market Imperfections and the Pricing Decision of Firms: Theory and Evidence", mimeo.
- [8] Chevalier J. A. and D. S. Scharfstein (1996): "Capital-Market Imperfections and Countercyclical Markups: Theory and Evidence", *The American Economic Review*, 86(4), 703-725.
- [9] Coluzzi, C., A. Ferrando and C. Martinez-Carrascal (2015): "Financing obstacles and growth: an analysis for euro area non-financial firms", *The European Journal of Finance*, 21 (10-11), 773-790.
- [10] Duca, I., J.M. Montero, M. Riggi and R. Zizza (2017): "I will survive. Pricing strategies of financially distressed firms", *Temi di Discussione 1106*, Bank of Italy.
- [11] ECB (2014): "Annual Report 2013".

- [12] Gilchrist S., R. Schoenle, J. Sim, E. Zakrajsek (2017): "Inflation Dynamics during the Financial Crisis", *American Economic Review*, Vol. 107(3), 785-823.
- [13] Gilchrist S., R. Schoenle, J. Sim, E. Zakrajsek (2016): "Financial Heterogeneity and Monetary Union", mimeo.
- [14] Gilchrist S. and E. Zakrajsek (2015): "Customer Markets and Financial Frictions: Implications for Inflation Dynamics", Proceedings: Economic Policy Symposium, Jackson Hole, Federal Reserve Bank of Kansas City.
- [15] Gottfries, N. (1991): "Customer Markets, Credit Market Imperfection and Real Price Rigidity", *Economica*, 58, 317-323.
- [16] Greene, William (2010): "Testing hypotheses about interaction terms in nonlinear models", *Economics Letters* 107, 291-296.
- [17] Hadlock C. J. and J. R. Pierce (2010): "New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index," *Review of Financial Studies*, 23 (5), 1909-1940.
- [18] Hart O. and J. Moore (1998): "Default and Renegotiation: A Dynamic Model of Debt," *Quarterly Journal of Economics*, 113(1), 1-41.
- [19] Kimura, T. (2013): "Why Do Prices Remain Stable in the Bubble and Bust Period?" *International Economic Journal*, 27(2), 157-177.
- [20] Lokshin, M. and Z. Sajaia (2011): "Impact of interventions on discrete outcomes: Maximum likelihood estimation of the binary choice models with binary endogenous regressors", *Stata Journal* 11.3, 368-385.
- [21] Montero J. M. and A. Urtasun (2014): "Price-Cost Markups in the Spanish Economy: a Microeconomic Approach," Banco de España Working Papers - 1407.
- [22] Robinson, J. (1933): "The Economics of Imperfect Competition", London: Macmillan.
- [23] Stock J. and M. Yogo (2005): "Testing for Weak Instruments in Linear IV Regression," In: Andrews DWK Identification and Inference for Econometric Models. New York: Cambridge University Press pp. 80-108.

- [24] Warner E. J. and R. B. Barsky (1995): "The Timing and Magnitude of Retail Store Markdowns: Evidence from Weekends and Holidays", *Quarterly Journal of Economics*, 110(2), 321-352.
- [25] Yellen, J. (2016): "Macroeconomic Research After the Crisis", speech delivered at "The Elusive 'Great' Recovery: Causes and Implications for Future Business Cycle Dynamics", 60th annual economic conference, Federal Reserve Bank of Boston, Boston, Massachusetts.

Tables and Figures

Table 1: Main predictions from DMRZ's model

Internally financed firms ($fc_i = 0$)	Externally financed firms ($fc_i = 1$)
$m_0 = f(\text{demand}, \nu, \alpha)$	$m_1 = g(\text{demand}, \nu, \alpha)$
$\lambda_0 \equiv \frac{\partial m_0}{\partial \text{demand}} \leq 0$	$\lambda_1 \equiv \frac{\partial m_1}{\partial \text{demand}} < 0$
$\frac{\partial \lambda_0}{\partial \nu} < 0$	$\frac{\partial \lambda_1}{\partial \nu} < 0$
$\frac{\partial \lambda_0}{\partial \alpha} < 0$	$\frac{\partial \lambda_1}{\partial \alpha} < 0$

Notes: m_j represents the level of markups for type j firm ($j = 0, 1$). The cyclical response of markups is given by $\lambda_j \equiv \partial m_j / \partial \text{demand}$. The parameter ν is the cyclical response of the elasticity of demand and α is the degree of persistence of demand shocks.

Table 2: Sectoral breakdown

Country name	Manufacturing	Construction	Trade	Business services
CZ	498	85	156	272
ES	506	0	600	851
IT	553	15	229	290
LU	54	129	113	165
LV	100	69	173	203
MT	32	9	26	72
PL	415	124	300	305
Size (#workers)				
5-19	519	146	855	1,047
20-49	608	139	431	492
50-199	573	100	220	381
200+	457	46	91	235

Notes: The definition of the sectors is based on NACE Rev.2. The business service category includes firms from transportation and storage; accommodation and food service activities; information and communication; real estate activities; professional, scientific and technical activities; and administrative and support service activities. Trade includes units from retail and wholesale trade.

Table 3: Descriptive statistics for treated/non-treated firms

Means (std.dev.)	Treated firms (2853)	Non-treated firms (3131)	Equal means (p-val.)
Increase in markups = 1	0.260 (0.439)	0.271 (0.445)	0.304
Sector (Manufacturing = 1)	0.413 (0.492)	0.399 (0.490)	0.284
Size (SME = 1)	0.897 (0.303)	0.843 (0.363)	0.000
Age	20.97 (14.48)	21.78 (14.78)	0.052
Ownership (Foreign = 1)	0.168 (0.374)	0.232 (0.422)	0.000
Subsidiary = 1	0.160 (0.367)	0.283 (0.451)	0.000
Structure (Multi-establ.=1)	0.190 (0.392)	0.250 (0.433)	0.000
Fall in demand = 1	0.541 (0.498)	0.437 (0.496)	0.000
Fall in competition = 1	0.080 (0.271)	0.060 (0.238)	0.003
Fall in volatility = 1	0.604 (0.489)	0.671 (0.470)	0.000

Notes: Treated (non-treated) firms are those for which $\hat{f}c=1$ ($\hat{f}c=0$). The manufacturing sector also includes construction firms. See the text for the definition of the different variables. The third column reports the p-value for a test of equality of means across both groups of firms.

Table 4: Estimation results for selection and outcome equations

	Selection equation	Non-treatment outcome ($fc=0$)	Treatment outcome ($fc=1$)
	Coeff. (s.e.)	Coeff. (s.e.)	Coeff. (s.e.)
Fall in demand = 1	-0.086 (0.203)	-0.738 (0.260)***	-0.713 (0.324)**
Fall in competition = 1	-0.110 (0.500)	-0.408 (0.182)**	-0.804 (0.326)***
Fall in volatility = 1	-0.603 (0.183)***	-0.119 (0.248)	-0.211 (0.274)
Fall in (demand & compet.)	0.294 (0.566)	0.256 (0.269)	1.142 (0.489)**
Fall in (demand & volat.)	0.376 (0.253)	0.291 (0.325)	0.593 (0.381)
Ownership (Foreign = 1)	-0.565 (0.164)***	0.608 (0.160)***	-0.202 (0.263)
Subsidiary = 1	-0.456 (0.165)***	0.386 (0.139)***	-0.579 (0.201)***
Structure (Multi-establ. = 1)	0.073 (0.109)	0.026 (0.191)	0.203 (0.208)
Age	-0.166 (0.046)***	-	-
$\{\rho_0, \rho_1\}$	-	-0.981 (0.018)***	0.983 (0.032)***
LR test independent errors ($H_0: \rho_0 = \rho_1 = 0$)	$\chi^2(2) = 28.28$ (p-val = 0.000)		
ATT		0.237 (0.230)	
Obs.		5147	

Industry, size and country dummies included but not reported. Robust standard errors in parentheses. Sampling weights. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Bootstrapped (200 replications) standard errors for ATT.

Table 5: Treatment effects on the treated by country

Country	# treated firms	ATT	Std. Dev.	Min	Max
CZ	237	0.265	0.152	0.034	0.673
ES	979	0.177	0.089	0.013	0.763
IT	459	0.099	0.080	0.008	0.530
LU	164	0.299	0.161	0.032	0.747
LV	38	0.524	0.167	0.117	0.922
MT	14	0.177	0.089	0.027	0.326
PL	614	0.391	0.135	0.051	0.875

Figure 1: Distribution of treatment effects by country

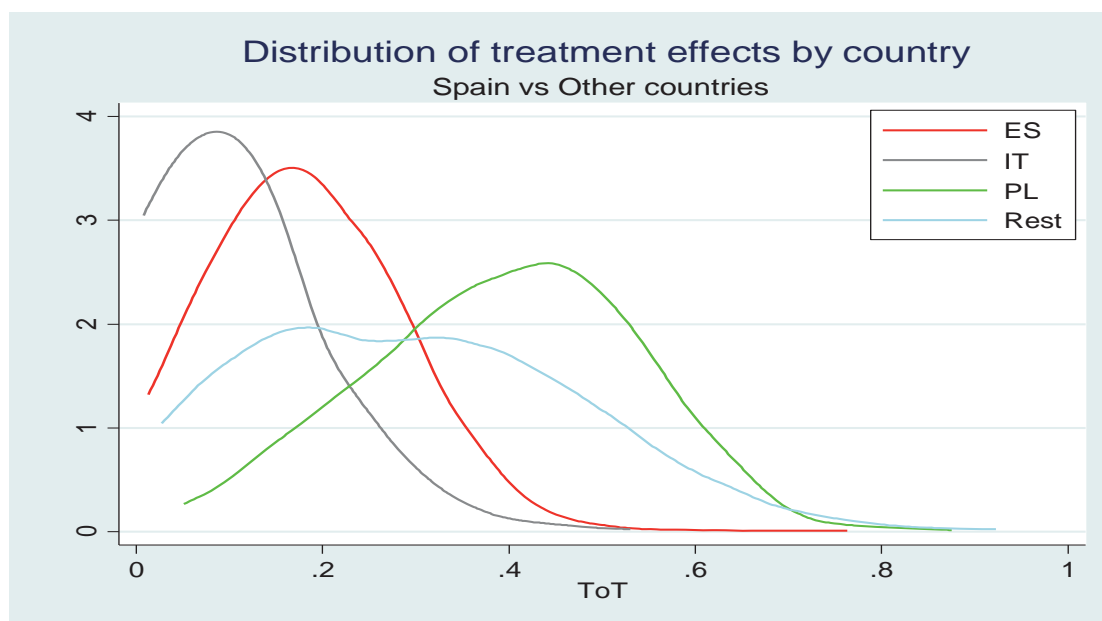


Table 6: Average partial effects (APE) of main regressors on $P(m = 1|fc, X)$

Panel A. $P(m = 1 fc = 0, X)$					
	APE (%stat.sig.)	Min. effect	Max. effect	Min. Wald test stat. (p-value)	Max. Wald test stat. (p-value)
Fall in demand = 1	-0.183 (92.1%)	-0.667	-0.011	0.000	0.493
Fall in (demand & compet.)	0.116 (25.1%)	-0.130	0.333	0.005	0.960
Fall in (demand & volatility)	0.093 (0.0%)	0.016	0.212	0.343	0.510
Panel B. $P(m = 1 fc = 1, X)$					
	APE (%stat.sig.)	Min. effect	Max. effect	Min. Wald test stat. (p-value)	Max. Wald test stat. (p-value)
Fall in demand = 1	-0.179 (88.7%)	-0.480	-0.012	0.000	0.499
Fall in (demand & compet.)	0.126 (34.6%)	0.025	0.321	0.000	0.603
Fall in (demand & volatility)	0.095 (0.0%)	0.007	0.222	0.343	0.439

APE: averaged across all relevant observations. In parentheses we report the share of APE that are statistically significant at a 10% level. Min/Max effects and Min/Max Wald tests based on values computed for each observation. Standard errors estimated by the Delta method.

Figure 2: Distribution of partial effects for the demand shock

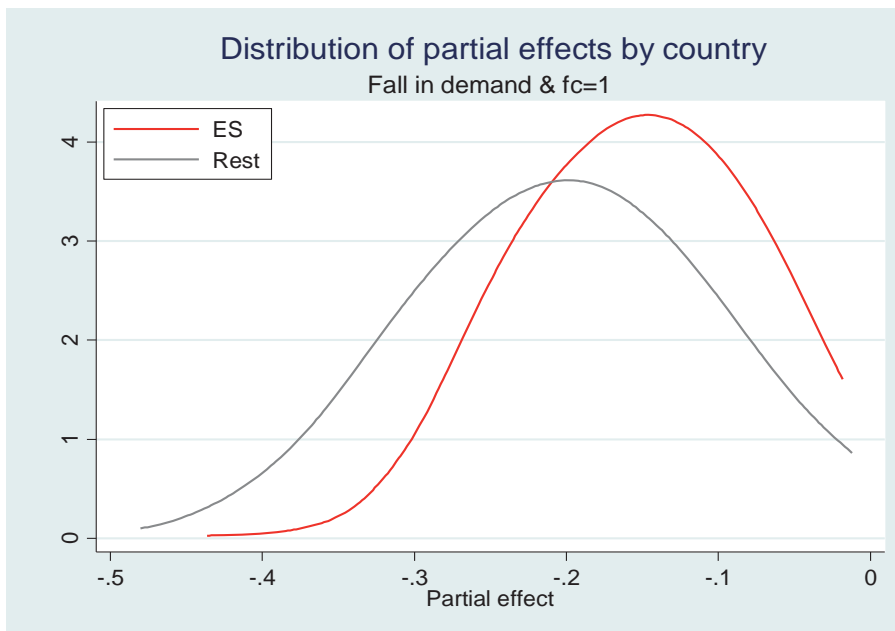
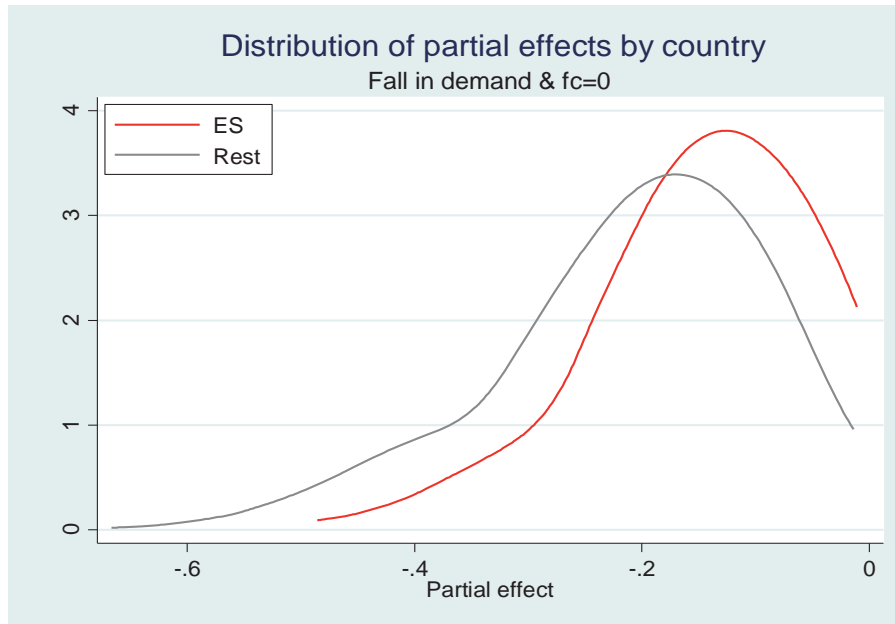


Table 7: Average Partial Effects for alternative specifications

Panel A. Manufacturing vs Market Services								
	Baseline: Manufacturing				Baseline: Mkt. Services			
	P(m = 1/fc=0, X)		P(m = 1/fc=1, X)		P(m = 1/fc=0, X)		P(m = 1/fc=1, X)	
	APE (%stat.sig.)	Min./Max. Effect	APE (%stat.sig.)	Min./Max. Effect	APE (%stat.sig.)	Min./Max. Effect	APE (%stat.sig.)	Min./Max. Effect
Fall in demand = 1	-0.175 (32.4%)	-0.791/0.186	-0.145 (38.1%)	-0.474/0.140	-0.187 (62.4%)	-0.600/-0.045	-0.183 (58.2%)	-0.662/-0.012
Fall in (dem. & compet.)	0.197 (33.5%)	0.024/0.454	0.164 (41.5%)	0.000/0.251	0.108 (0.8%)	-0.164/0.331	0.110 (3.4%)	0.027/0.404
Fall in (dem. & volat.)	0.256 (99.9%)	0.022/0.665	0.211 (100%)	0.000/0.382	0.041 (0%)	-0.003/0.103	0.042 (0%)	-0.003/0.156
ATT		0.244 (0.148)*				0.239 (0.289)		
No. observations		2096				3051		
Panel B. Sampling weights								
	No sampling weights				Employment weights			
	P(m = 1/fc=0, X)		P(m = 1/fc=1, X)		P(m = 1/fc=0, X)		P(m = 1/fc=1, X)	
	APE (%stat.sig.)	Min./Max. Effect	APE (%stat.sig.)	Min./Max. Effect	APE (%stat.sig.)	Min./Max. Effect	APE (%stat.sig.)	Min./Max. Effect
Fall in demand = 1	-0.158 (96.3%)	-0.426/-0.046	-0.132 (95.4%)	-0.221/-0.040	-0.162 (82.6%)	-0.366/-0.013	-0.186 (88.2%)	-0.394/-0.016
Fall in (dem. & compet.)	0.068 (0%)	0.035/0.149	0.057 (0%)	0.024/0.077	0.124 (0%)	0.043/0.170	0.141 (0%)	0.044/0.184
Fall in (dem. & volat.)	0.033 (0%)	0.009/0.102	0.037 (1.0%)	0.010/0.070	0.053 (0%)	-0.004/0.200	0.063 (0%)	-0.014/0.214
ATT		0.239 (0.235)				0.196 (0.358)		
No. observations		5147				5147		

Table 7: Continued.

Panel C. Small vs Medium&Large firms								
	Baseline: Small firms				Baseline: Medium&Large firms			
	P($m = 1/fc=0, X$)		P($m = 1/fc=1, X$)		P($m = 1/fc=0, X$)		P($m = 1/fc=1, X$)	
	APE (%stat.sig.)	Min./Max. Effect	APE (%stat.sig.)	Min./Max. Effect	APE (%stat.sig.)	Min./Max. Effect	APE (%stat.sig.)	Min./Max. Effect
Fall in demand = 1	-0.178 (77.6%)	-0.643/-0.009	-0.169 (80.6%)	-0.507/-0.013	-0.169 (96.1%)	-0.342/-0.041	-0.229 (95.1%)	-0.381/-0.072
Fall in (demand & compet.)	0.115 (23.4%)	-0.106/0.338	0.115 (33.5%)	0.021/0.329	0.097 (0%)	0.050/0.139	0.121 (0%)	0.066/0.156
Fall in (demand & volat.)	0.097 (0%)	0.014/0.225	0.096 (0%)	0.008/0.242	0.013 (0%)	-0.025/0.147	0.052 (2.2%)	-0.077/0.21
ATT		0.248 (0.215)				0.260 (0.278)		
No. observations		3465				1682		

APE: averaged across all relevant observations. In parentheses we report the share of APE that are statistically significant at a 10% level. Min/Max effects based on values computed for each observation. Standard errors estimated by the Delta method, except for the ATT (which are bootstrapped, 200 replications).

Figure 3: Distribution of treatment effects by country. Manufacturing vs Services

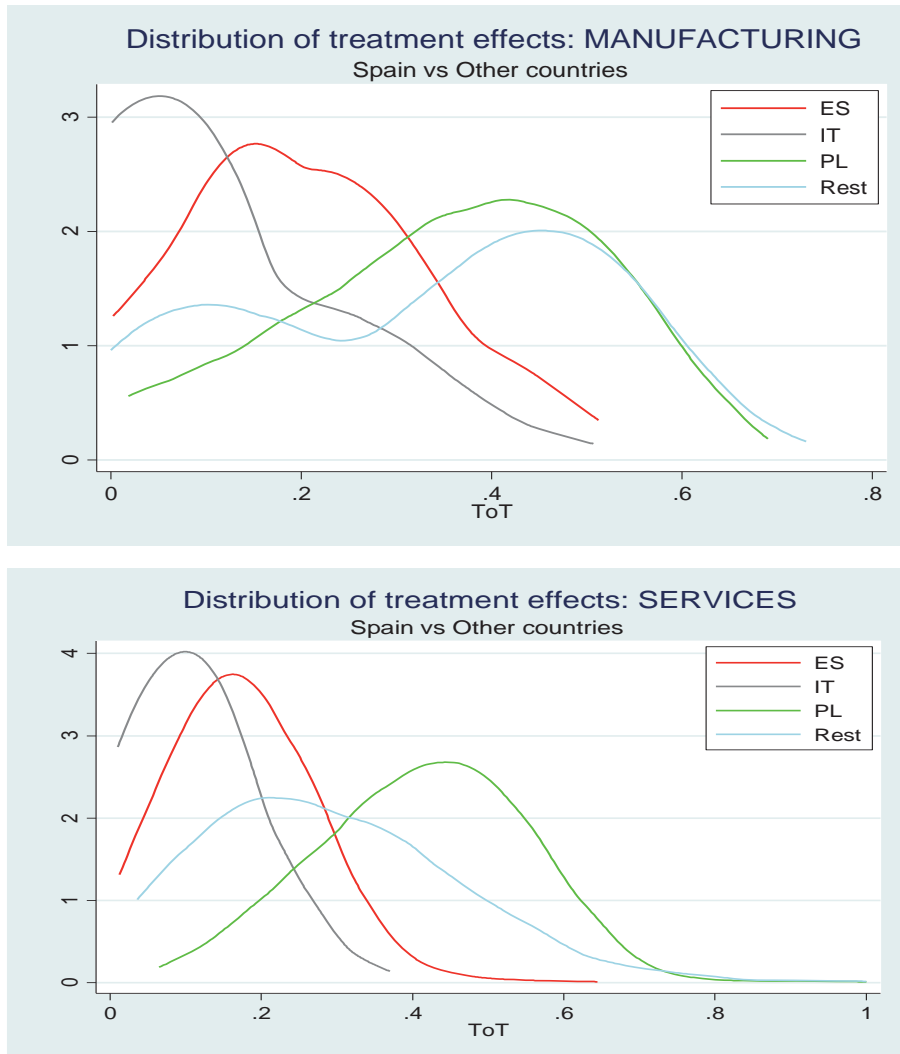


Table 8: Results for alternative estimators: linear models

	2SLS	OLS <i>fc</i> = 0	OLS <i>fc</i> = 1
<i>fc</i> (= ATT)	0.207 (0.342)		
Fall in demand = 1	-0.284 (0.092)***	-0.341 (0.096)***	-0.243 (0.119)**
Fall in (demand & compet.)	0.294 (0.128)**	0.096 (0.069)	0.449 (0.176)***
Fall in (demand & volat.)	0.183 (0.115)	0.237 (0.111)**	0.125 (0.149)
R²	0.107	0.135	0.126
Age (First stage)	-0.065 (0.022)***		
First-stage F-stat.	8.80		
Cragg-Donald Wald stat.	10.49		
No. observations	5147	2694	2466

Notes: All the regressions include the same RHS variables than in Table 4. They are omitted for the sake of simplicity. The first-stage F statistic is computed for the excluded instrument (Age). The Cragg-Donald Wald statistic must be compared with Stock and Yogo's (2005) critical values. For a rejection rate of at most 10% and 15% these critical values are 16.38 and 8.96, respectively.

Annex A: Theoretical model

In this annex I provide a detailed description of the model developed in Duca, Montero, Riggi and Zizza (2017, DMRZ hereafter), which is in turn based on Chevalier and Scharfstein (1996, CS hereafter). It is a spatial competition model with consumer switching costs extended with capital market imperfections.

A.1 The model

There are two firms $k = A, B$, who compete for two periods $\tau = 1, 2$. There is a mass of consumers, normalized to 1, who reside uniformly on the line segment $[0, 1]$, with firm A located at 0 and firm B located at 1. Each shopper has a reservation price R for one unit of a good produced by A or B . Only one type of good is bought and sold. In the first period consumers bear a transportation cost of t per unit of distance traveled²⁰ along the line to the firm of their choice. These costs are zero in the second period, but consumers develop switching costs, s , because of their first-period purchases.

As a first novelty, DMRZ follow Warner and Barsky (1995) and assume that each consumer purchases θ_H or $\theta_L < \theta_H$ units of the good per period instead of one unit, as in CS. This way the shopping volume per consumer increases (decreases) in booms (recessions), which delivers a procyclical elasticity of demand. This means that firms perceive stronger competition in expansions than during downturns. The idea of a procyclical elasticity of demand dates back to Robinson (1933) and it was taken up more recently by Bils (1989), Rotemberg and Woodford (1991) and Warner and Barsky (1995).²¹

Both firms produce with a constant marginal cost c and set first-period prices before they know the demand realization. For each firm, first-period demand can be high ($\theta_1 =$

²⁰ Alternatively, it can be interpreted as measuring how far each firm's product is from a consumer's ideal set of product characteristics.

²¹ Bils (1989) uses a customer-market model in which the inflow of new customers more responsive to prices generates a higher demand elasticity in booming periods. He provides indirect evidence on the cyclical importance of new, more price-elastic consumers, at an aggregate level and for retailers of electrical appliances. Warner and Barsky (1995), in turn, propose a different mechanism: retailers perceive their demand to be more elastic in the high demand states, because in such periods consumers are more vigilant and better informed. This would explain a well-known micro puzzle: the tendency for markdowns to occur when shopping intensity is exogenously high, like in weekends or prior to Christmas, as it allows sharing fixed costs of shopping across purchases. On the empirical side, Field and Pagoulatos (1997) provide empirical evidence of a procyclical price elasticity of demand for a panel of 38 US food manufacturing industries from 1972 to 1987; whereas Riggi and Santoro (2015) find that the elasticity of demand increased after 1999 in Italy in the wake of a demand stimulus.

θ_H) with probability μ , or low ($\theta_1 = \theta_L$) with probability $(1 - \mu)$. As a second novelty, DMRZ assume that firms attribute a certain probability α to the event that the first-period state of demand will persist in the future.²² In other words, $Pr(\theta_\tau = \theta_{\tau-1}) = \alpha$. The values of μ and α are the same for both firms.

Finally, to compete in this market firms must invest an amount I at the beginning of the first period.

In order to solve the model, it has to be taken into account that in the second period, when consumers' switching costs have already been built up, a fraction σ_1^A of the consumers has bought firm A 's product in $\tau = 1$, while a fraction $\sigma_1^B = 1 - \sigma_1^A$ has previously purchased B 's product. In this context, Klemperer (1995) shows that each firm can charge the consumer's reservation price R in the second period without fear of being undercut by its rival, provided that switching costs s are high enough. The intuition is that the rival firm would have to cut its price a discrete amount below $R-s$ and, while it may sell more units at this lower price, it earns less profits on its own locked-in first-period customers.

Internally financed firms

The first case considered by DMRZ is when firms are financed with internally generated funds. Let's denote with p_τ^k the price charged by firm k in period τ . Second-period profits for each firm k depend on their first-period market shares:

$$\pi_2^k(\sigma_1^k, p_2^k, \theta_2) = (R - c) \theta_2 \sigma_1^k \quad (\text{A1})$$

To evaluate the market shares in period 1, one must calculate the location y_i^* (with $i = H, L$) of the shopper who is indifferent between A and B :

$$p_1^A \theta_i + t y_i = p_1^B \theta_i + t(1 - y_i)$$

or

$$y_i^* = \frac{(p_1^B - p_1^A) \theta_i}{2t} + \frac{1}{2} \quad (\text{A2})$$

From (A2), one can get that the fraction of consumers that buy from A and B in period 1 are given by:

$$\sigma_1^A = \frac{(p_1^B - p_1^A) \theta_1}{2t} + \frac{1}{2} = 1 - \sigma_1^B \quad (\text{A3})$$

²² CS assume no uncertainty for the second-period demand, which is normalized to one.

and first-period profits for firm A can be written as:

$$\pi_1^A(p_1^A, p_1^B, \theta_1) = (p_1^A - c)\theta_1\sigma_1^A(\theta_1) \quad (\text{A4})$$

At the beginning of the first period, each firm simultaneously and non-cooperatively chooses prices, given its conjecture about its rival price, and before knowing the demand realization (i.e. before the customers arrive to the store), to maximize total discounted future profits:

$$V^A = (p_1^A - c)\bar{\theta}_1\sigma_1^A(\bar{\theta}_1) + (R - c)\bar{\theta}_2\sigma_1^A(\bar{\theta}_1) \quad (\text{A5})$$

where it is assumed that the discount factor is 1 and $\bar{\theta}_1$ and $\bar{\theta}_2$ are firm's expectations formulated at the beginning of time 1 for first- and second-period demand, respectively.²³

Maximizing expression (A5) with respect to the first-period price, it is obtained firm A 's pricing reaction curve as a function of firm B 's price:

$$p_1^A = \frac{p_1^B + c}{2} + \frac{t}{2\bar{\theta}_1} - \frac{\bar{\theta}_2(R - c)}{2\bar{\theta}_1} \quad (\text{A6})$$

implying that prices are strategic complements (i.e. firm A 's optimal price is increasing in its rival's price). Then, the symmetric equilibrium ($p_1^A = p_1^B$) when both firms are internally financed is:

$$p_1^* = c + \frac{t}{\bar{\theta}_1} - \frac{\bar{\theta}_2(R - c)}{\bar{\theta}_1} \quad (\text{A7})$$

and the markup of price over marginal cost (defined as $m = p - c$) is:

$$m_1^* = \frac{t}{\bar{\theta}_1} - \frac{\bar{\theta}_2(R - c)}{\bar{\theta}_1} \quad (\text{A8})$$

To gain some intuition, it is interesting to discuss the difference between the equilibrium markup that emerges in equation (A8) and the one in CS, which is $m_1^{CS} = t - \frac{(R - c)}{\bar{\theta}_1}$. First, in their framework, in a one-period setting, each firm would charge a markup t , while in the current version of the model, the markup would instead be equal to $t/\bar{\theta}_1$. This difference comes from having assumed that consumers wish to buy a different number of units depending on being in a period of boom or bust. As a consequence, the travel cost they are willing to bear varies with the volume of goods they wish to purchase.

²³ They are defined as $\bar{\theta}_1 = \mu\theta_H + (1 - \mu)\theta_L$ and $\bar{\theta}_2 = [\mu\alpha + (1 - \mu)(1 - \alpha)]\theta_H + [(1 - \mu)\alpha + \mu(1 - \alpha)]\theta_L$.

This means that, when firms expect high demand, they perceive greater competition for their market area, i.e. a higher elasticity of demand affecting pricing behavior. Note that the demand elasticity in a symmetric equilibrium is given by:

$$\eta \equiv -\frac{\partial y_1}{\partial p_1} \frac{p_1}{y_1} = \frac{\bar{\theta}_1 p_1^*}{t}$$

which is clearly procyclical, as it can be shown that $v \equiv \partial \eta / \partial \mu = (\theta_H - \theta_L) p_1^* / t > 0$.²⁴

Second, in a two-period setting price margins are lowered by $\frac{\bar{\theta}_2(R-c)}{\theta_1}$ in the DMRZ framework and by $\frac{(R-c)}{\theta_1}$ in CS. This difference comes from having assumed a variable second-period demand ($\bar{\theta}_2$ vs one), whose expected level matters for firms' incentive to compete for first-period market shares, on which they can later charge the monopoly price R .

DMRZ follow CS and think of μ as measuring the level of demand, so that the cyclicity of price margins can be measured by $\partial m_1^* / \partial \mu$. After some algebra, this derivative is:

$$\lambda \equiv \frac{\partial m_1^*}{\partial \mu} = \frac{(\theta_H - \theta_L)(R-c)}{\bar{\theta}_1^2} \left[(\theta_H + \theta_L)(1 - \alpha) - \frac{t}{(R-c)} \right] \quad (\text{A9})$$

Thus, markups can be either procyclical ($\lambda > 0$) or countercyclical ($\lambda < 0$), depending on the values of the parameters of the model.²⁵ Markups might be procyclical, i.e. fall in recessions, because the fall in current demand relative to future demand makes it more appealing to invest in market shares by cutting prices and increase monopoly profits in the future, when demand will be relatively high.

However, the two additional channels considered would weaken the procyclical behavior of markups. As it is evident from equation (A9), $\partial \lambda / \partial \alpha < 0$; i.e. the higher the expected persistence of demand, the less procyclical (or the more countercyclical) are price margins. Intuitively, when the low (high) state of demand is expected to persist in

²⁴ The elasticity of demand in CS is acyclical and given by p_1^* / t .

²⁵ This expression is similar to that in CS, except for the term in brackets, which is absent in their model.

0	1	2
Firms form their expectations on θ_1 and θ_2 , and set P_1 conditional on these expectations	Firms observe π_1 . If $\pi_1 < D$, the assets are liquidated, and firms' pay off is π_1 . If $\pi_1 > D$, firms pay out D and set $P_2 = R$.	Firms, who paid out D , get π_2

Figure 1: Model timeline

the future, the relative convenience of lowering current markups to reap profits in the future, rather than in the present, is weaker (stronger).

Moreover, it can be shown that $\frac{\partial \lambda}{\partial v} = -\frac{t}{\eta \theta_1} < 0$, which means that the more procyclical is the elasticity of demand, the less procyclical (or the more countercyclical) are price markups. Intuitively, when the elasticity of demand falls very much in downturns, the gain in demand from a given price cut is diminished. Thus, this reduces the benefit from investing in market shares by cutting prices during recessions. In other words, in order to achieve a given level of present demand and, given switching costs, of future profits, the firm has to incur in a larger price decrease, thus harming current profits.

Financially constrained firms

In the model with capital-market imperfections, firms need to raise I externally. DMRZ follow CS and introduce financial frictions following Bolton and Scharfstein (1990, 1996) and Hart and Moore (1998), who build an incomplete-contracts model in which corporate cash flows, while being observable to the manager and to investors, cannot be verified by outside parties (i.e. a judge). Thus, contracts are incomplete and cannot be contingent on firms' performance. Further, an additional friction is that the manager can costlessly divert all project returns to himself, but cannot divert the firms' productive assets.

As in Hart and Moore (1998), the allocation of foreclosure rights is crucial for the solution of this type of model. The only way to get managers to pay out cash flow is to threaten to liquidate the firm's assets if they do not; however, liquidation is inefficient in the sense that assets are transferred away from the entrepreneur who can extract the most value from them. This means that firm's assets are worth a fraction $\xi < 1$ of the remaining cash flow if managed by investors. As Hart and Moore (1998) and Bolton and Scharfstein (1996) show, the optimal contract resembles a real-world debt contract, as it calls for a fixed payment of D at date 1; if no repayment is made, the investor has the right to seize and liquidate the project's assets.

The manager is restrained from diverting cash flow in period 1, and incentivized to pay out D , by the prospect of diverting all of the period 2 cash flow to himself. From these assumptions, one can derive the incentive compatibility as $D \leq \pi_2^k$. In the case when the project does not generate enough returns ($D > \pi_1^k$), then the manager would choose to pay nothing and have the assets liquidated. Therefore, the entrepreneur's total payoff would only be π_1^k . As in CS, and consistently with the conjecture that firms are more likely to be liquidity-constrained in recessions, it is assumed that $\pi_1^k(\theta_L) < D < \pi_1^k(\theta_H)$. See Figure 1 for the timing structure of the model.

Let us define $\pi_{1L}^k \equiv \pi_1^k(\theta_L)$ as the first-period level of profit when demand is low, while $\pi_{1H}^k \equiv \pi_1^k(\theta_H)$ when demand is high. The expected second-period profits, conditional on having a high and a low level of demand in the first period, are denoted as $\pi_{2/1H}$ and $\pi_{2/1L}$, respectively. Then, the investors' participation constraint, which ensures that their expected payoffs are nonnegative, can be written as: $\mu D + (1 - \mu)\xi\pi_{2/1L} - I \geq 0$. Competition among investors ensures that the previous condition is met with equality. The optimal contract is designed such that it is consistent with product market equilibrium in periods 1 and 2. Thus, the value of D in equilibrium, $D^* = \frac{I - (1 - \mu)\xi\pi_{2/1L}}{\mu}$, cannot be larger than $\pi_{2/1H}$ for the contract to be both incentive compatible and feasible. It is thus assumed for the remainder that $D^* \leq \pi_{2/1H}$.

In this setting, firm A chooses p_1^A to maximize the expected payoff over the two periods, defined as: $V^A = \mu[\pi_{1L}^k - D + \pi_{2/1H}^k] + (1 - \mu)\pi_{1L}^A$, taking D and p_1^B as given. The first-order condition results from equalizing (A10) to zero:

$$\frac{\partial V^A}{\partial p_1^A} = \mu \left[\frac{\partial \pi_{1H}^k}{\partial p_1^A} + \frac{\partial \pi_{2/1H}^k}{\partial p_1^A} \right] + (1 - \mu) \frac{\partial \pi_{1L}^A}{\partial p_1^A} \quad (\text{A10})$$

Let us denote $\bar{\theta}_{2/1H} \equiv \alpha\theta_H + (1 - \alpha)\theta_L$ the expected demand in the second period conditional on having a high demand level in the first one. From condition (A10), the symmetric equilibrium when both firms are externally financed implies that:

$$p_1^* = c + \frac{\bar{\theta}_1}{\Gamma} t - \mu \frac{\bar{\theta}_{2/1H}\theta_H}{\Gamma} (R - c) \quad (\text{A11})$$

and the equilibrium markup is:

$$m_1^* = \frac{\bar{\theta}_1}{\Gamma} t - \mu \frac{\bar{\theta}_{2/1H}\theta_H}{\Gamma} (R - c) \quad (\text{A12})$$

where $\Gamma \equiv \mu\theta_H^2 + (1 - \mu)\theta_L^2 = E(\theta_1^2)$. It is not straightforward to compare equations (A11) and (A12) with equations (A7) and (A8). In the CS model it is shown that the equilibrium price (markup) is higher when firms are externally financed than when they are internally financed. In this setting, firms are less interested in building market share because they earn less in some states of nature (the firm is liquidated in low-demand states).

The cyclical nature of price markups when firms are financially constrained is given by the following expression:

$$\lambda \equiv \frac{\partial m_1^*}{\partial \mu} = -\frac{\theta_H\theta_L(R-c)}{\Gamma^2} \left[\bar{\theta}_{2/1H}\theta_L + \frac{t(\theta_H - \theta_L)}{(R-c)} \right] < 0 \quad (\text{A13})$$

or equivalently:

$$\lambda \equiv \frac{\partial m_1^*}{\partial \mu} = -\frac{\theta_H\theta_L(R-c)}{\Gamma^2} \left[\bar{\theta}_{2/1H}\theta_L + \frac{t\nu\bar{\theta}_1}{\eta} \right] < 0 \quad (\text{A14})$$

Thus, when firms are financially constrained markups are always countercyclical. Intuitively, during recessions, the possibility of liquidation makes firms care less about the future; they prefer extracting rents today by setting a higher price rather than building market shares to enhance future profits.

Regarding the expected persistence of demand, its impact on markup cyclicity operates only through $\pi_{2/1H}$ and it can be shown that $\partial\lambda/\partial\alpha < 0$. Thus, when the firm expects a booming period to persist in the future, the relative appeal of lowering current markups to reap profits in the future, rather than in the present, is stronger, thus reinforcing the degree of countercyclicity.

Additionally, it is straightforward to show that $\partial\lambda/\partial\nu < 0$. The more procyclical is the elasticity of demand, the more countercyclical are price margins. Again, the intuition is the same as before: the more the elasticity of demand falls in slumps, the more firms become insulated from competition and the smaller becomes the gain in demand for a given price decrease. This reduces the benefit from investing in market shares (by cutting prices) during recessions.

A.2 Additional references

- [1] Bils, Mark (1989): "Pricing in a Customer Market." *The Quarterly Journal of Economics*, 104(4), 699-718.
- [2] Bolton P. and D. S. Scharfstein (1990): "A theory of Predation Based on Agency Problems in Financial Contracting", *American Economic Review*, 80(1), 93-106.
- [3] Bolton P. and D. S. Scharfstein (1996): "Optimal Debt Structure and the Number of Creditors", *Journal of Political Economy*, 104(1), 1-25.
- [4] Field, Martha K., and Emilio Pagoulatos (1997): "The cyclical behavior of price elasticity of demand", *Southern Economic Journal*, 64(1): 118-129.
- [5] Klemperer, P. (1995): "Competition When Consumers Have Switching Costs - An Overview with Applications to Industrial Organization, Macroeconomics, and International Trade," *Review of Economic Studies*, 62(4), 515-539.
- [6] Motta, M. (2004): "Competition Policy: Theory and Practice", Cambridge University Press, Cambridge, UK.
- [7] Riggi, M. and S. Santoro (2015): "On the Slope and the Persistence of the Italian Phillips Curve", *International Journal of Central Banking*, 11(2), 157-197.

Annex B: WDN survey questions about the main variables used in the empirical exercise

- **m = 1/0:**

NC.2.7_b How did the following factors evolve in your firm during 2010-2013?

Prices (as compared to total costs):

1=Strong decrease; 2=Moderate decrease; 3=Unchanged; 4=Moderate increase; 5=Strong increase

- **fc = 1/0:**

C.2.3 With regard to finance, please indicate for 2010-2013 how relevant were for your firm each one of the following events? *Note: credit here refers to any kind of credit, not only bank credit* [1=Not relevant; 2=Of little relevance; 3=Relevant; 4=Very relevant]

1. Credit was not available to finance:

- working capital
- new investment
- refinance debt

2. Credit was available, but conditions (interest rate and other contractual terms) were too onerous to finance:

- working capital
- new investment
- refinance debt

- **low_demand = 1/0:**

C.2.6 How did [...] demand for your main product evolve during 2010-2013? [1=Strong decrease; 2=Moderate decrease; 3=Unchanged; 4=Moderate increase; 5=Strong increase]

- Domestic demand for your main product/service
- Foreign demand for your main product/service

- **low_volat. = 1/0:**

C.2.1 How did the following factors affect you firm's activity during 2010-2013? [1=Strong decrease; 2=Moderate decrease; 3=Unchanged; 4=Moderate increase; 5=Strong increase]

- Volatility/uncertainty of demand for your products/services

- **low_competition = 1/0:**

NC.5.5 Compared to the situation before 2008, how has the competitive pressure on your main product domestic and foreign markets changed in the period 2010-2013? [1=Strong decrease; 2=Moderate decrease; 3=Unchanged; 4=Moderate increase; 5=Strong increase]

- a. Domestic market
- b. Foreign market

BANCO DE ESPAÑA PUBLICATIONS

WORKING PAPERS

- 1601 CHRISTIAN CASTRO, ÁNGEL ESTRADA and JORGE MARTÍNEZ: The countercyclical capital buffer in Spain: an analysis of key guiding indicators.
- 1602 TRINO-MANUEL NÍGUEZ and JAVIER PEROTE: Multivariate moments expansion density: application of the dynamic equicorrelation model.
- 1603 ALBERTO FUERTES and JOSÉ MARÍA SERENA: How firms borrow in international bond markets: securities regulation and market segmentation.
- 1604 ENRIQUE ALBEROLA, IVÁN KATARYNIUK, ÁNGEL MELGUIZO and RENÉ OROZCO: Fiscal policy and the cycle in Latin America: the role of financing conditions and fiscal rules.
- 1605 ANA LAMO, ENRIQUE MORAL-BENITO and JAVIER J. PÉREZ: Does slack influence public and private labour market interactions?
- 1606 FRUCTUOSO BORRALLO, IGNACIO HERNANDO and JAVIER VALLÉS: The effects of US unconventional monetary policies in Latin America.
- 1607 VINCENZO MERELLA and DANIEL SANTABÁRBARA: Do the rich (really) consume higher-quality goods? Evidence from international trade data.
- 1608 CARMEN BROTO and MATÍAS LAMAS: Measuring market liquidity in US fixed income markets: a new synthetic indicator.
- 1609 MANUEL GARCÍA-SANTANA, ENRIQUE MORAL-BENITO, JOSEP PIJOAN-MAS and ROBERTO RAMOS: Growing like Spain: 1995-2007.
- 1610 MIGUEL GARCÍA-POSADA and RAQUEL VEGAS: Las reformas de la Ley Concursal durante la Gran Recesión.
- 1611 LUNA AZAHARA ROMO GONZÁLEZ: The drivers of European banks' US dollar debt issuance: opportunistic funding in times of crisis?
- 1612 CELESTINO GIRÓN, MARTA MORANO, ENRIQUE M. QUILIS, DANIEL SANTABÁRBARA and CARLOS TORREGROSA: Modelling interest payments for macroeconomic assessment.
- 1613 ENRIQUE MORAL-BENITO: Growing by learning: firm-level evidence on the size-productivity nexus.
- 1614 JAIME MARTÍNEZ-MARTÍN: Breaking down world trade elasticities: a panel ECM approach.
- 1615 ALESSANDRO GALESÌ and OMAR RACHEDÌ: Structural transformation, services deepening, and the transmission of monetary policy.
- 1616 BING XU, ADRIAN VAN RIXTEL and HONGLIN WANG: Do banks extract informational rents through collateral?
- 1617 MIHÁLY TAMÁS BORSI: Credit contractions and unemployment.
- 1618 MIHÁLY TAMÁS BORSI: Fiscal multipliers across the credit cycle.
- 1619 GABRIELE FIORENTINI, ALESSANDRO GALESÌ and ENRIQUE SENTANA: A spectral EM algorithm for dynamic factor models.
- 1620 FRANCISCO MARTÍ and JAVIER J. PÉREZ: Spanish public finances through the financial crisis.
- 1621 ADRIAN VAN RIXTEL, LUNA ROMO GONZÁLEZ and JING YANG: The determinants of long-term debt issuance by European banks: evidence of two crises.
- 1622 JAVIER ANDRÉS, ÓSCAR ARCE and CARLOS THOMAS: When fiscal consolidation meets private deleveraging.
- 1623 CARLOS SANZ: The effect of electoral systems on voter turnout: evidence from a natural experiment.
- 1624 GALO NUÑO and CARLOS THOMAS: Optimal monetary policy with heterogeneous agents.
- 1625 MARÍA DOLORES GADEA, ANA GÓMEZ-LOSCOS and ANTONIO MONTAÑÉS: Oil price and economic growth: a long story?
- 1626 PAUL DE GRAUWE and EDDIE GERBA: Stock market cycles and supply side dynamics: two worlds, one vision?
- 1627 RICARDO GIMENO and EVA ORTEGA: The evolution of inflation expectations in euro area markets.
- 1628 SUSANA PÁRRAGA RODRÍGUEZ: The dynamic effect of public expenditure shocks in the United States.
- 1629 SUSANA PÁRRAGA RODRÍGUEZ: The aggregate effects of government incometransfer shocks - EU evidence.
- 1630 JUAN S. MORA-SANGUINETTI, MARTA MARTÍNEZ-MATUTE and MIGUEL GARCÍA-POSADA: Credit, crisis and contract enforcement: evidence from the Spanish loan market.

- 1631 PABLO BURRIEL and ALESSANDRO GALES: Uncovering the heterogeneous effects of ECB unconventional monetary policies across euro area countries.
- 1632 MAR DELGADO TÉLLEZ, VÍCTOR D. LLEDÓ and JAVIER J. PÉREZ: On the determinants of fiscal non-compliance: an empirical analysis of Spain's regions.
- 1633 OMAR RACHEDI: Portfolio rebalancing and asset pricing with heterogeneous inattention.
- 1634 JUAN DE LUCIO, RAÚL MÍNGUEZ, ASIER MINONDO and FRANCISCO REQUENA: The variation of export prices across and within firms.
- 1635 JUAN FRANCISCO JIMENO, AITOR LACUESTA, MARTA MARTÍNEZ-MATUTE and ERNESTO VILLANUEVA: Education, labour market experience and cognitive skills: evidence from PIAAC.
- 1701 JAVIER ANDRÉS, JAVIER J. PÉREZ and JUAN A. ROJAS: Implicit public debt thresholds: an empirical exercise for the case of Spain.
- 1702 LUIS J. ÁLVAREZ: Business cycle estimation with high-pass and band-pass local polynomial regression.
- 1703 ENRIQUE MORAL-BENITO, PAUL ALLISON and RICHARD WILLIAMS: Dynamic panel data modelling using maximum likelihood: an alternative to Arellano-Bond.
- 1704 MIKEL BEDAYO: Creating associations as a substitute for direct bank credit. Evidence from Belgium.
- 1705 MARÍA DOLORES GADEA-RIVAS, ANA GÓMEZ-LOSCOS and DANILO LEIVA-LEON: The evolution of regional economic interlinkages in Europe.
- 1706 ESTEBAN GARCÍA-MIRALLES: The crucial role of social welfare criteria for optimal inheritance taxation.
- 1707 MÓNICA CORREA-LÓPEZ and RAFAEL DOMÉNECH: Service regulations, input prices and export volumes: evidence from a panel of manufacturing firms.
- 1708 MARÍA DOLORES GADEA, ANA GÓMEZ-LOSCOS and GABRIEL PÉREZ-QUIRÓS: Dissecting US recoveries.
- 1709 CARLOS SANZ: Direct democracy and government size: evidence from Spain.
- 1710 HENRIQUE S. BASSO and JAMES COSTAIN: Fiscal delegation in a monetary union: instrument assignment and stabilization properties.
- 1711 IVÁN KATARYNIUK and JAIME MARTÍNEZ-MARTÍN: TFP growth and commodity prices in emerging economies.
- 1712 SEBASTIAN GECHERT, CHRISTOPH PAETZ and PALOMA VILLANUEVA: Top-down vs. bottom-up? Reconciling the effects of tax and transfer shocks on output.
- 1713 KNUT ARE AASTVEIT, FRANCESCO FURLANETTO and FRANCESCA LORIA: Has the Fed responded to house and stock prices? A time-varying analysis.
- 1714 FÁTIMA HERRANZ GONZÁLEZ and CARMEN MARTÍNEZ-CARRASCAL: The impact of firms' financial position on fixed investment and employment. An analysis for Spain.
- 1715 SERGIO MAYORDOMO, ANTONIO MORENO, STEVEN ONGENA and MARÍA RODRÍGUEZ-MORENO: "Keeping it personal" or "getting real"? On the drivers and effectiveness of personal versus real loan guarantees.
- 1716 FRANCESCO FURLANETTO and ØRJAN ROBSTAD: Immigration and the macroeconomy: some new empirical evidence.
- 1717 ALBERTO FUERTES: Exchange rate regime and external adjustment: an empirical investigation for the U.S.
- 1718 CRISTINA GUILLAMÓN, ENRIQUE MORAL-BENITO and SERGIO PUENTE: High growth firms in employment and productivity: dynamic interactions and the role of financial constraints.
- 1719 PAULO SOARES ESTEVES and ELVIRA PRADES: On domestic demand and export performance in the euro area countries: does export concentration matter?
- 1720 LUIS J. ÁLVAREZ and ANA GÓMEZ-LOSCOS: A menu on output gap estimation methods.
- 1721 PAULA GIL, FRANCISCO MARTÍ, JAVIER J. PÉREZ, ROBERTO RAMOS and RICHARD MORRIS: The output effects of tax changes: narrative evidence from Spain.
- 1722 RICARDO GIMENO and ALFREDO IBÁÑEZ: The eurozone (expected) inflation: an option's eyes view.
- 1723 MIGUEL ANTÓN, SERGIO MAYORDOMO and MARÍA RODRÍGUEZ-MORENO: Dealing with dealers: sovereign CDS comovements.
- 1724 JOSÉ MANUEL MONTERO: Pricing decisions under financial frictions: evidence from the WDN survey.