Markups and markdowns

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ABSTRACT

This paper studies the high yet undocumented incidence of firms displaying markups lower than unity, i.e., prices lower than marginal costs, for protracted periods of time. Using a large sample of French manufacturing firms for the period 1990-2007, the paper estimates markups at the firm level and documents the extent to which firms exhibit negative price cost margins. The paper is able to provide an explanation for this phenomenon using the option value approach to investment decisions. The results suggest that firms facing higher investment irreversibility tend to continue operating even when prices fall below marginal costs as they wait for market conditions to improve. This effect is magnified in the presence of uncertainty.

KEY WORDS

Markups, irreversibility, uncertainty, negative price-cost margins, French manufacturing data.

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D22, D24, D81, E22, L11.

Markups and markdowns*

1. Introduction

Recent advances in empirical industrial organisation have equipped researchers with the ability to estimate time-varying, firm-level price-cost margins. Since the seminal contribution by De Loecker (2011) and De Loecker and Warzynski (2012), several papers have explored the determinants of markups, their evolution and their relationship with productivity, quality, international activities of firms and other relevant variables (De Loecker and Goldberg, 2014; Collard-Wexler and De Loecker, 2015; Bellone et al., 2016; De Loecker et al., 2016; Caselli et al., 2017).

This paper starts from the observation that, for protracted periods of time, several firms display markups lower than unity, i.e., prices lower than marginal costs or negative price-cost margins, which we label markdowns. The analysis documents the size of this phenomenon using a large sample of French manufacturing firms for the period 1990-2007. To the best of our knowledge, this is the first paper analysing the presence and persistence of negative price-cost margins at the firm level.

This apparently odd behaviour can be rationalized in multiple ways. A first possible explanation is strategic dumping by firms, which decide to price below marginal costs in order to expand production and conquer market shares. The possible rationale can be either to exploit economies of scale, especially in the presence of learning effects (see, for instance, Timoshenko, 2015 for an investigation on the effect of learning on export persistence), or to drive competitors out of business. The ability to sustain temporary losses would then be related to firm size.

However, an explanation based exclusively on optimal strategic behaviour by firms is difficult to reconcile with the non-negligible fraction of firms that display markdowns for a long period. Rather, this phenomenon may suggest the inability of market selection mechanisms to efficiently allocate resources and push less productive and less successful firms out of the market. Sunk entry costs may act as a barrier to market selection and, thus, as a determinant of productivity differences across surviving firms (Fariñas and Ruano, 2005). The lack of effective market selection was first discussed with respect to Japanese "zombie firms" to explain the very slow economic recovery after the burst of the bubble in the early 1990s (Caballero et al., 2008; Fukuda and Nakamura, 2011; Kwon et al., 2015). It has recently re-gained centre stage thanks to a series of papers by the OECD that try to explain the productivity slowdown in terms of a less efficient market selection (see, for instance, Andrews et al., 2016; McGowan et al., 2017).

We contribute to this recent stream of literature by presenting empirical evidence pointing to an increased incidence of markdowns over time, consistent with the notion that market selection might be less efficient. The explanation that we favour, and bring to the data in the empirical analysis, is rooted in the option value approach to investment decisions. In a series of landmark contributions to investment theory, Dixit and Pindyck show that investment decisions based on the net present value may not be correct in the presence of irreversibility (see for instance Dixit, 1992, and Dixit and Pindyck, 1994). As Dixit (1992, p. 107) puts it, "firms stay in business for lengthy periods while absorbing operating losses, and price can fall substantially below average variable cost without inducing disinvestment

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or exit". The main lesson by Dixit and Pindyck (1994) is that the presence of sunk costs, i.e., investment irreversibility, produces a zone of inaction, whereby firms prefer (and rightly so) to wait and see, rather than engaging in an investment/disinvestment decision. Moreover, they show that uncertainty reinforces this kind of behaviour by widening the zone of inaction and increasing the "value of waiting".

In the case under investigation here, we hypothesise that firms (that appreciate this value of waiting) are ready to absorb some losses in order to retain the ability to serve a certain market and make profits once economic conditions improve. Then, our research question is whether the presence of irreversibility and uncertainty affects the likelihood and extent of markdowns. Indeed, the results suggest that firms facing higher irreversibility are more likely to continue operating even when prices fall below marginal costs and this effect is magnified by the presence of uncertainty.

The paper is organised as follows. Section 2 describes the data, the methodology used to estimate markups and some statistics on the incidence of markdowns. Section 3 shows the results of a regression analysis on the determinants of negative price-cost margins. Section 4 provides some concluding remarks.

2. Data and estimation of markups

2.1. Data sources

We use data on a large sample of French manufacturing firms based on the *Enquête Annuelle d'Entreprises* (EAE), an annual survey that gathers information for manufacturing firms with at least 20 employees. The survey was conducted by the French Ministry of Industry until 2007, which is the latest available year. After some basic cleaning, we have information for over 36,000 firms covering the period 1990-2007.[1]

The EAE, whose unit of observation is the firm (not the plant), contains information on the value of total sales, capital stock and materials, the number of hours worked by employees, profits and exports as well as the 4-digit industry in which the firm produces. Real values of sales, capital and materials are obtained using 2-digit industry deflators provided by the French national statistical office (INSEE).

INSEE also compiles the industry depreciation rates that we use to proxy for irreversibility following Chirinko and Schaller, 2009 and Guariglia et al., 2012. We construct a dummy variable set to unity if the depreciation rate at the three-digit industry level is lower than the median value. The motivation for using this variable is that, when firms find it costly to sell unwanted capital, they can still reduce it via depreciation. However, this is less likely to occur in industries with low depreciation rates, implying that in such industries firms are more likely to face investment irreversibility.

As a measure of uncertainty, we use the root-mean-squared error (RMSE) of a second-order autoregression of sales (Alesina et al., 2003). This is measured at the firm level and it

[1] We eliminate from the sample companies that only appear for a single year and those that have a ratio of intermediate inputs over sales smaller than 0.05 or greater than 2.

is invariant over time. As a robustness check we also experiment with alternative measures of dispersion of either sales or profits (always at the firm-level): the coefficient of variation of sales; the range of annual growth of sales within the sample period; the RMSE of a second-order autoregression of profits.

2.2. Estimation of markups

In order to study how the incidence of negative price-cost margins is affected by irreversibility and uncertainty, we first need to consistently estimate time-varying firm-level markups.

The methodology is derived from De Loecker and Warzynski (2012) and it has been analysed further in several recent works (De Loecker and Goldberg, 2014; De Loecker et al., 2016). The approach assumes that firms minimise costs and at least one input is adjusted freely (materials), while the other factors may show frictions in their adjustment (capital and labour). Unlike previous contributions, however, this framework neither imposes constant returns to scale nor requires the computation of the user cost of capital. Moreover, following the approach of using inputs to control for unobservables in production function estimations (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015), we assume that productivity is Hicks-neutral and specific to the firm.

De Loecker and Warzynski (2012) derive a simple expression for markups from a firm's cost minimisation problem. This expression is given by

$$\mu_{it} = \theta_{it}^{m} \left(\alpha_{it}^{m}\right)^{-1}, \tag{1}$$

where μ_{it} is the markup of firm i at time t, θ_{it}^{m} is the output elasticity of materials (superscript m), and α_{it}^{m} is the revenue share of materials. While it is straightforward to compute the latter from the data, the estimation of the output elasticity of materials is more demanding as it relies on estimates of a production function, assumed here to be Cobb-Douglas.

In order to get unbiased estimates of the output elasticity of materials at the firm-year level, we consider the following general production function for firm i in industry s at time t:

$$y_{it} = f_s\left(l_{it}, k_{it}, m_{it}; \beta\right) + \omega_{it} + \varepsilon_{it}, \tag{2}$$

where y_{it} is the natural logarithm of real sales of firm i at time t, l_{it}, k_{it} and m_{it} are respectively the natural logarithms of the quantities of labour, capital and materials used by the firm and that get transformed into the output according to the production function f_s, β is the parameter vector to be estimated in order to calculate the output elasticities, ω_{it} is the firm-level productivity term that is observable by the firm but not by the econometrician and ε_{it} is an error term that is unobservable to both the firm and the econometrician. The function f_s is assumed to be Cobb-Douglas and it is allowed to change across two-digit sectors, as implied by the subscript s. Thus, the parameter vector β is made up of three parameters for each sector.

Different estimators can be used to estimate the production function in equation (2). The preferred estimator in this paper is the Wooldridge-Levinsohn-Petrin (WLP) estimator, as derived from Wooldridge (2009) and implemented in Petrin and Levinsohn (2012).

The WLP estimator is related to the approach of using inputs to control for unobserved productivity shocks in production function estimations. The introduction of lagged values of specific inputs as proxies for productivity addresses potential endogeneity issues related to the simultaneous determination of inputs and unobserved productivity, as suggested by Wooldridge (2009). Moreover, this estimator does not assume constant returns to scale, is robust to the Ackerberg et al. (2015) criticism of the Levinsohn and Petrin (2003) estimator and is programmed as a simple instrumental variable estimator.

The WLP estimator requires the variables affecting the productivity process to be specified. Following Petrin and Levinsohn (2012), it is assumed that productivity is a function of a second-order polynomial in the natural logarithms of lagged capital and materials. In addition, following De Loecker (2013), we include in the productivity process the potential effects of plants' international trade status on productivity via a dummy for exporting. Year fixed effects are also included to take into account time-variant shocks common to all plants. All these additional regressors are not included in the function f_s.

After having estimated the production function parameters β based on the Cobb-Douglas specification, the output elasticity of materials can be calculated by simply taking the estimated parameter on materials at the sector level. Using these estimates of the output elasticity of materials and the calculated revenue shares of materials, it is possible to calculate markups at the firm-year level based on equation (1). Moreover, using the same estimates of the production function parameters, it is possible to compute productivity as the difference between observed and expected output. Thus, estimated productivity is given by:

$$\hat{\omega}_{it} = y_{it} - f_s\left(l_{it}, k_{it}, m_{it}; \hat{\beta}\right), \tag{3}$$

where the terms with a hat are estimated. As noted by Petrin and Levinsohn (2012), this estimate of productivity includes the error term ε_{it}. However, as long as this error term is pure noise and uncorrelated with the variables in the production function, this does not bias the results, but it may lead to larger standard errors in the second stage of our analysis, when productivity is employed as an independent variable.

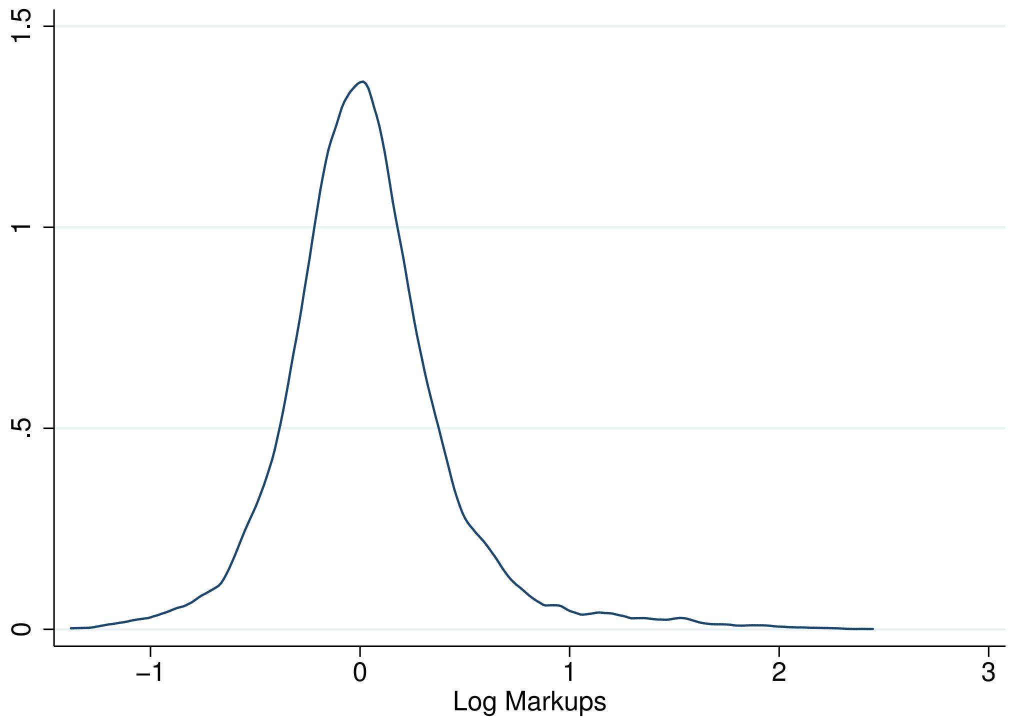
2.3. Descriptive statistics

Next, we provide some descriptive statistics for markups, document the extent to which plants exhibit markdowns and show how markdowns differ by irreversibility and uncertainty.

Figure 1 shows the distribution of the point estimates for markups in year 2000. The figure clearly shows that there are many observations displaying markdowns, amounting to 46% of all observations in the sample. Moreover, about 69% of all firms have markups lower than unity in at least one year.[2] A similar picture is observed by taking the distribution of markups for any other year, although after 2000 the number of observations with markdowns

[2]Making use of the estimates of the standard errors of the production function parameters clustered at the firm level, we can calculate the 95% confidence intervals for markups. Based on the upper bound values, rather than the point estimates, of markups, 39% of all observations exhibit markdowns and 62% of all firms exhibit markdowns in at least one year.

Figure 1: Distribution of markups, 2000



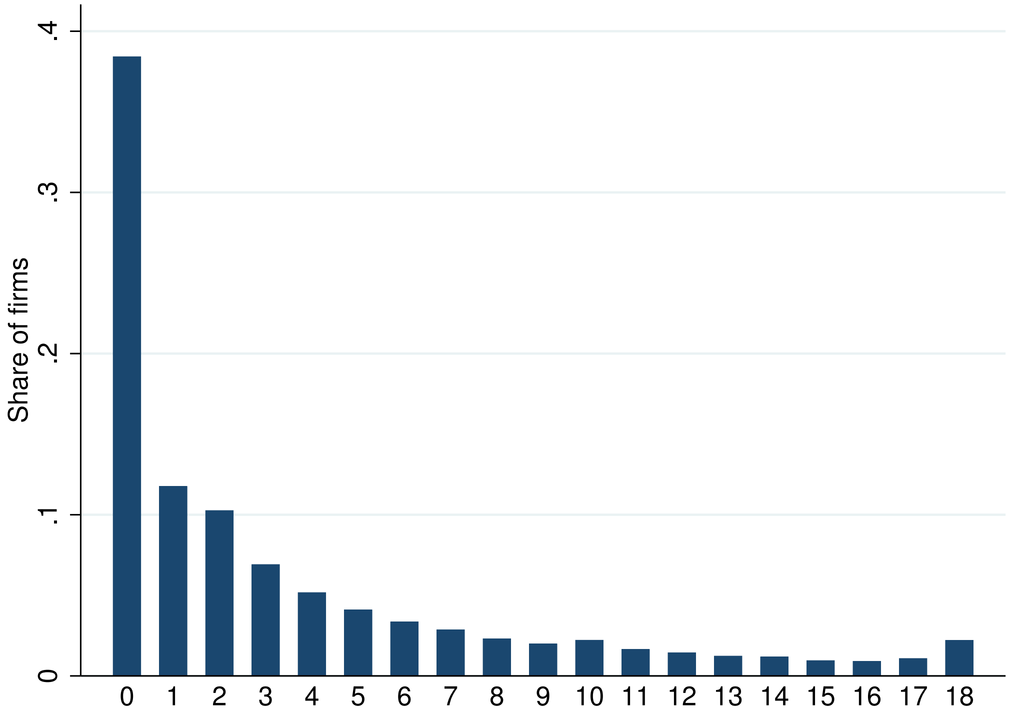
Source: Own estimations using French manufacturing data from *Enquête Annuelle d'Entreprises* and the WLP estimator of the production function.

increases, which is consistent with the evidence of diminishing market selection in Berlingieri et al. (2017). This large number of observations with markdowns is not only a feature of the French manufacturing data and is also observed for the case of India (De Loecker and Goldberg, 2014; De Loecker et al., 2016) and Mexico (Caselli et al., 2017). In these countries, markdowns account for about 25% to 45% of observations.

Based on the markups' estimates, we consider two measures of the incidence of markdowns within firms over time. The first one is the total number of years in which firm i's upper bound values of markups are lower than unity, $\mu_i^{tot<1}$, and the second one is the maximum number of consecutive years in which firm i's upper bound values of markups are lower than unity, $\mu_i^{cons<1}$. The two measures are highly correlated, with a value of 0.96. In the rest of the paper, the preferred measure is the total number of years with markdowns, but the results do not change qualitatively when the maximum number of consecutive years with markdowns is used.

Figure 2 shows the share of firms by the total number of years with markdowns. Over 60% of firms exhibit markdowns in at least one year, half of which display negative price-cost margins in at least five years. Moreover, over 10% of firms exhibit markdowns in at least ten years and over 2% of firms display markdowns in all eighteen years for which data are available.

Figure 2: Share of firms by number of years with markdowns



Source: Own estimations using French manufacturing data from *Enquête Annuelle d'Entreprises* and the WLP estimator of the production function.

Next, we show some descriptive statistics by dividing firms into two groups: those that never exhibit markups lower than unity (Markdown = 0) and those that go through at least one year with markups lower than unity (Markdown = 1). Table 1 shows the average and standard deviations for sales, number of hours worked (labour), capital stock, productivity and profitability (profit over sales), and presents t-tests and Kolmogorov-Smirnov tests for the differences in average values and distributions between the two groups of firms. Both on average and across the distributions, firms that exhibit markdowns tend to be larger, more productive and employ more workers and capital, while their profitability is significantly lower. While at first sight this result may seem at odds with the literature suggesting that larger and more productive firms tend to have higher markups, we need to point out that these are unconditional statistics and only a more formal analysis, as conducted in the next section, can establish how these variables are related to each other. On the other hand, as this paper hypotheses, this result seems to suggest that firms incurring in losses and yet staying in the market are not simply poorly-performing firms, but rather this may be a rational choice of profit-maximising firms facing a negative shock. Moreover, the fact that several firms' characteristics differ depending on whether firms exhibit a markdown in at least one year justifies an econometric model that treats differently the probability of exhibiting a markdown and the extent of such markdowns, as we do in the next section.

Table 1: Descriptive statistics by markdown

	Sales	Labour	Capital	ω_{it}	Profitability
Markdown = 0	25949.9	213963.4	8112.8	0.51	0.08
	(328368.8)	(1043701)	(128590)	(0.45)	(0.10)
Markdown = 1	33154.3	254968.9	10372.4	0.60	0.06
	(386618.6)	(1428437)	(146780.1)	(0.37)	(0.10)
t-test	-5.28	-8.44	-4.33	-61.51	64.17
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
K-S test	0.28	0.12	0.17	0.11	0.10
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: The table reports the average values and standard deviations (in parentheses) for the five variables in the columns by the presence of markdowns in at least one year, the t-tests (p-values in parentheses) for the differences in their average values and the Kolmogorov-Smirnov (K-S) tests (p-values in parentheses) for the differences in their distributions. The variables are: sales (1000s Euros), labour (number of hours worked), capital stock (1000s Euros), productivity, ω_{it}, and profitability (profits/sales). The number of observations is 322,970.

Table 2: Markups and productivity by irreversibility

	μ_{it}	$\mu_{it}^{<1}$	$\mu_{i}^{tot<1}$	ω_{it}
Irreversibility = 0	1.25	0.22	2.66	0.30
	(0.61)	(0.41)	(4.30)	(0.44)
Irreversibility = 1	1.13	0.47	5.85	0.69
	(0.74)	(0.50)	(5.93)	(0.32)
t-test	45.21	-138.89	-43.22	-277.52
	(0.00)	(0.00)	(0.00)	(0.00)
K-S test	0.22	0.25	0.25	0.49
	(0.00)	(0.00)	(0.00)	(0.00)

Notes: The table reports the average values and standard deviations (in parentheses) for the four variables in the columns by irreversibility, the t-tests (p-values in parentheses) for the differences in their average values and the Kolmogorov-Smirnov (K-S) tests (p-values in parentheses) for the differences in their distributions. The variables are: μ_{it} is the point estimate of markups for firm i at time t, $\mu_{it}^{<1}$ is a dummy variable set to unity if the observation shows an upper bound value of its markup lower than unity, $\mu_{i}^{tot<1}$ is the total number of years in which firm i's upper bound values of markups are lower than unity and ω_{it} is productivity. Irreversibility is a dummy variable at the industry level set to unity if the depreciation rate at the three-digit industry level is lower than the median value. The number of observations is 322,970.

Table 2 shows averages (and standard deviations in parentheses) for markups, markdowns, total number of years with markups lower than unity and productivity by our measure of irreversibility. The table also displays the values of the t-tests and Kolmogorov-Smirnov tests for the differences in average values and distributions by irreversibility. The tests show that, on average and across the whole distributions, firms facing higher irreversibility have smaller markups and higher productivity, but, more importantly, a larger number of years with markdowns. This is *prima facie* evidence in favour of the hypothesis that firms facing higher irreversibility are more likely to continue operating even when prices fall below marginal costs.

Similar to Table 2, Table 3 shows averages (and standard deviations in parentheses) for

Table 3: Markups and productivity by irreversibility and uncertainty

	μ_{it}	$\mu_{it}^{<1}$	$\mu_i^{tot<1}$	ω_{it}
Irreversibility = 0 & Uncertainty = 0	1.28	0.20	2.44	0.32
	(0.61)	(0.40)	(4.40)	(0.45)
Irreversibility = 1 & Uncertainty = 1	1.10	0.50	6.13	0.67
	(0.69)	(0.50)	(5.69)	(0.32)
t-test	47.83	-115.42	-44.04	-178.69
	(0.00)	(0.00)	(0.00)	(0.00)
K-S test	0.28	0.30	0.40	0.45
	(0.00)	(0.00)	(0.00)	(0.00)

Notes: The table reports the average values and standard deviations (in parentheses) for the four variables in the columns by irreversibility and uncertainty, the t-tests (p-values in parentheses) for the differences in their average values and the Kolmogorov-Smirnov (K-S) tests (p-values in parentheses) for the differences in their distributions. The variables are: μ_{it} is the point estimate of markups for firm i at time t, $\mu_{it}^{<1}$ is a dummy variable set to unity if the observation shows an upper bound value of its markup lower than unity, $\mu_i^{tot<1}$ is the total number of years in which firm i's upper bound values of markups are lower than unity and ω_{it} is productivity. Irreversibility is a dummy variable at the industry level set to unity if the depreciation rate at the three-digit industry level is lower than the median value. Uncertainty is a dummy variable at the firm level set to unity when the root-mean-squared error of a second-order autoregression of sales is above the median value in each industry. The number of observations is 165,832.

markups, markdowns, total number of years with markups lower than unity and productivity by the interaction of irreversibility and uncertainty. Uncertainty is measured as a dummy variable at the firm level equal to one when the root-mean-squared error of a second-order autoregression of sales is above the median value in each industry. The table also displays the values of the t-tests and Kolmogorov-Smirnov tests for the differences in average values and distributions by irreversibility and uncertainty. The tests show that, both on average and across the whole distributions, firms facing higher irreversibility coupled with higher uncertainty in terms of sales have smaller markups and higher productivity and are more likely to go through longer periods with markdowns. This is evidence in favour of the hypothesis that the effect of irreversibility on markdowns is magnified by uncertainty.

3. Empirical analysis

This section tests how irreversibility and uncertainty affect the incidence of markdowns using regression analysis. As one of the main explanatory variables, namely our measure of uncertainty, is time-invariant within a firm, the analysis makes use of the cross-section of firms, rather than the panel.

Therefore, we estimate the following equation:

$$\mu_i^{tot<1} = h\left(\gamma_0 + \gamma_1 unc_i + \gamma_2 irr_s + \gamma_3 unc_i \times irr_s + \gamma_4 \mathbf{X}_i + \eta_s\right) + \epsilon_i, \tag{4}$$

where $\mu_i^{tot<1}$ is the total number of years in which firm i's upper bound values of markups are lower than unity, unc_i represents a measure of uncertainty at the firm level, irr_s is a measure of irreversibility at the industry level, $\mathbf{X}_i$ is a vector of additional regressors, η_s

represents three-digit industry fixed effects, function h depends on the underlying model chosen to estimate equation 4 and ϵ_i is an error term. The vector of additional regressors $\mathbf{X}$, contains average values over time within firms of sales, labour, capital and productivity.

It should be noticed that the parameter γ_2 cannot be identified directly in equation 4 because it is perfectly collinear with the industry fixed effects η_s. Therefore, in all regressions below we employ the fixed effects filtered estimation method by Pesaran and Zhou (2016) to retrieve the estimates of the coefficient on the irreversibility variable. This method is implemented by estimating equation 4, retrieving the industry fixed effects and finally regressing the estimates of the industry fixed effects on the irreversibility variable and a constant. In this case, standard errors are not an issue because, as discussed below, we use a bootstrapping method to estimate unbiased standard errors (for an alternative estimation method, see Klaassen and Teulings, 2015).

Given that our dependent variable takes non-negative integer values, we expect linear regression not to be an appropriate estimation technique, as it fails to take into account the limited number of possible values of the response variable (Cameron and Trivedi, 2013). In this context, count data models can be used and it is possible to test which specific model provides the best fit of the data. To this end, we estimate equation 4 using several models and we provide tests to guide our choice.

3.1. Model Selection

Besides the linear regression, we model the number of markdowns using Poisson, negative binomial II (NB-II), zero-inflated and hurdle regressions. As will be evident from the various tests, the NB-II model is preferred to the Poisson model in all cases considered because of the presence of overdispersion, i.e., the conditional variance exceeds the conditional mean, thereby contradicting one of the assumptions of the Poisson model. Moreover, the relatively large incidence of zero counts and the results in Table 1 call for the use of models that relax the assumption that the zeros and the positives come from the same data-generating process, such as the zero-inflated and hurdle models. In fact, Table 1 already suggests that the two sub-samples of firms are different.[3] [4]

[3] Both the zero-inflated and the hurdle models supplement the count density with a binary process for whether the observation takes zero or positive counts, which we parametrise through a logit model using the same set of regressors. The difference between them is related to how the zero counts are to be interpreted. In the zero-inflated model the zero counts occur in two ways, i.e., as a realization of the binary process and as a realisation of the count process. Thus, this model is mainly used when many zeros are present, although having many zeros in the dataset does not automatically mean that a zero-inflated model is necessary (Cameron and Trivedi, 2010). On the other hand, the hurdle model has the interpretation that zero and positive counts come from separate and potentially independent decision-making processes. Therefore, while the full sample of observations is used in the binary decision process, only the positive counts are included in the count density using a distribution truncated at zero.

[4] We have also tried a Heckman-type approach, by estimating first a probit regression with an exclusion restriction and then including the calculated inverse Mills ratio in a negative binomial II regression with only positive counts. The results are qualitatively similar to those of the hurdle model. However, we do not report this estimation as we believe that the Heckman model does not provide a good representation of the data-generating process given that there is no actual censoring in this case.

Table 4 reports the estimates of equation 4 based on the following regressions: ordinary least squares (OLS, column 1), negative binomial II (NB-II, column 2), zero-inflated negative binomial II (ZINB-II, columns 3 and 4, corresponding respectively to the inflated logit regression, which determines the probability of observing a zero outcome, and the augmented NB-II regression) and logit-truncated NB-II hurdle (Hurdle, columns 5 and 6, corresponding respectively to the logit regression, which determines the probability of a positive outcome, and the truncated NB-II regression). The table shows two-step block bootstrapped standard errors to obtain unbiased and consistent estimates of the standard errors in the presence of generated variables, such as markups, the measures of uncertainty and productivity (Ashraf and Galor, 2013; Caselli, 2016).

The table reports several statistics and tests to help us choosing the model with the best fit. First, all regressions reported are significant overall, as indicated by the large and statistically significant F-statistics in the case of OLS and LR χ^2 for the count data models. In order to examine the fit of the conditional mean for count data models, rather than focusing on the McFadden's pseudo R-squared, which is noneheless reported, it is more interesting to look at the squared correlation between fitted and actual counts (R^2 fit/actual counts). This is equivalent to the standard R-squared for the OLS case. We obtain values ranging from 0.04 for the NB-II model to 0.28 for the hurdle model based on the NB-II, thus favouring the hurdle model over the others. It should be noticed, however, that the squared correlation of fitted and actual counts is larger in all Poisson-based regressions (bottom part of Table 4), for which we do not report the corresponding coefficients. This is the only statistic and test that favours the Poisson-based models over the NB-II-based models.

Besides looking at the fit for the conditional mean, we can also investigate the fit for the overall probability distribution of the number of markdowns by calculating the sum over all counts of the absolute deviations of the fitted probability from the actual cell frequency (Deviation fit/actual counts). A large deviation between the fitted frequency and the observed sample frequency for a given count indicates a lack of fit. This statistic confirms that the NB-II model provides the worst fit with a value of 0.25, while the zero-inflated and hurdle models based on the NB-II provide a better fit, both with a value of 0.18. The values for the corresponding Poisson regressions are much higher, suggesting a poor fit of the probability distribution.

The Akaike information criterion (AIC) and the Bayesian information criterion (BIC) provide further statistics to be used for our model selection. Lower values of these estimates suggest that a model is to be preferred relative to the others used to fit the same set of data. According to the AIC and the BIC, once again the hurdle model seems to be the best model for this analysis, ahead of the zero-inflated model and the standard NB-II model. Moreover, it should be noticed that the models based on the NB-II regression are always preferred to those based on the Poisson regression. The AIC and the BIC also make evident the poor quality of the linear regression.

3.2. Estimation results

Having established that our preferred estimation is based on the hurdle model, combining logit and truncated NB-II regressions, we can move on to the discussion of the coefficient

Table 4: Markdowns, irreversibility and uncertainty: model selection

	OLS	NB-II	ZINB-II		Hurdle	
			Inflated	NB-II	Logit	Tr. NB-II
RMSE sales	1.37***	1.22***	-3.45***	0.89***	2.63***	0.42***
	(0.55)	(0.15)	(0.68)	(0.18)	(0.24)	(0.11)
Irreversibility	4.47***	2.97***	-1.46***	2.38***	5.96***	1.15***
	(0.50)	(0.18)	(0.41)	(0.22)	(0.23)	(0.10)
RMSE sales × Irreversibility	2.05***	-0.03	-2.31***	-0.15	0.71**	0.26**
	(0.77)	(0.17)	(0.74)	(0.18)	(0.32)	(0.13)
Sales	4.03***	2.12***	-4.56***	1.51***	4.34***	1.06***
	(0.26)	(0.08)	(0.31)	(0.10)	(0.13)	(0.06)
Labour	-2.68***	-1.36***	3.32***	-0.97***	-3.06***	-0.68***
	(0.24)	(0.06)	(0.21)	(0.07)	(0.09)	(0.04)
Capital	-0.14	-0.17***	0.57***	-0.09***	-0.44***	-0.03*
	(0.09)	(0.02)	(0.07)	(0.02)	(0.03)	(0.02)
Productivity	-4.33***	-4.12***	4.70***	-2.90***	-8.91***	-1.58***
	(0.67)	(0.26)	(0.48)	(0.30)	(0.33)	(0.18)
α (dispersion parameter)		0.81***		0.61***		0.56***
		(0.05)		(0.04)		(0.02)
Industry fixed effects	yes	yes	yes	yes	yes	yes
No of obs.	30470	30470	30470	30470	30470	18923
R^2/Pseudo R^2	0.62	0.13	0.07		0.16	
F-statistics/LR χ^2	490.11	18702.00	10001.07		23094.57	
R^2 fit/actual counts		0.04	0.21		0.28	
Deviation fit/actual counts		0.25	0.18		0.18	
AIC	169304.5	125569.9	123870.9		120691.0	
BIC	170128.6	126402.4	124928.1		122339.3	
Poisson regressions						
R^2 fit/actual counts		0.30	0.40		0.39	
Deviation fit/actual counts		0.57	0.34		0.52	
AIC		164115.1	145649.6		140487.4	
BIC		164939.3	146698.4		142127.4	

Notes: The dependent variable is the total number of years with markups lower than unity (markdowns) at the firm level. The variables sales, labour, capital and productivity are measured as averages over time within firms. Two-step bootstrapped standard errors clustered at the plant level and stratified at the sector level are shown in parentheses (500 repetitions). *, ** and *** indicate coefficients significantly different from zero at the 10%, 5% and 1% level respectively.

estimates. Focusing firstly on the main variable of interest, Table 4 shows that the dummy for irreversibility is positive and statistically significant in all estimations, with the exception of the inflated part of the zero-inflated model. However, a negative coefficient in the estimation in column 3 is equivalent to a positive coefficient in the other estimations (and vice-versa) given that the logit regression in this case determines the probability of a zero outcome rather than that of a positive outcome. Based on the hurdle model, the positive coefficient on the irreversibility variable implies not only that firms in industries with more irreversible investment tend to be more likely to display a markdown in at least one year, but also exhibit a larger number of years with markdowns. The potential channel through which this relationship works is related to the fact that when firms face a negative shock, i.e., price falls below marginal cost, and selling capital is costly, i.e., investment is irreversible, firms tend to stay in the market waiting for market conditions to improve rather than exit the market.

What is more, the interaction between uncertainty (measured by RMSE sales) and irreversibility is also positive and significant in the estimations of the hurdle model, while it is not significant in the NB-II and ZINB-II models. The positive coefficient implies that firms facing more irreversible investment coupled with more uncertainty in their sales are more likely to go through at least one year with a markdown and tend to withstand more years with markups lower than unity. This implies that an uncertain environment magnifies the effect of irreversibility on the tendency of firms to stay in the market waiting for conditions to improve even though they are incurring in losses, as the option value theory predicts.

With regards to the other variables, the preferred measure of uncertainty (RMSE sales) always exhibits positive and statistically significant coefficients. This is a rather mechanic result as it simply implies that firms that have more dispersed sales over time are also more likely to incur in losses, which last for longer. As expected, markups are also more likely to fall below unity and to stay below unity for more years for firms with fewer employees, less capital stock and lower productivity, all features associated with worse firm performance. On the other hand, larger firms in terms of sales are more likely to exhibit markdowns and to face them for more years. This result can be explained by pointing out that large firms may be better able to cope with negative shocks as they have greater access to external financing and, thus, are able to stay in the market for longer even when facing losses for several years.[5] Lastly, we report the dispersion parameter, α, of the NB-II distribution. This parameter is constrained to zero in Poisson models, while it is allowed to differ from zero in NB-II models, with positive values implying overdispersion. In all regressions, the dispersion parameter is positive and statistically different from zero, which provides further evidence that the NB-II model is more appropriate than the Poisson model.

3.3. Robustness Checks

Next, we check for the robustness of our key results, namely that irreversibility has a positive effect on the probability of encountering markdowns and on their count and this effect is magnified by uncertainty, in a variety of specifications. In all specifications shown below, we use the hurdle model, combining logit and truncated NB-II regressions, to estimate the coefficients of the determinants of markdowns as it was previously found to have the best fit.

Table 5 provides a set of robustness checks based on three alternative measures of uncertainty: the coefficient of variation of sales (CV sales), the range of annual growth of sales within the sample period (Range sales growth), the RMSE of a second-order autoregression of profits (RMSE profits).

[5]As a robustness check, we include sales, labour, capital stock and productivity in different combinations to test if the exclusion of one or more of them affects the signs of the coefficients of the others. Results are not affected qualitatively and are available upon request.

Table 5: Markdowns and irreversibility: alternative measures of uncertainty

	CV sales		Range sales growth		RMSE profits	
	Logit	Tr. NB-II	Logit	Tr. NB-II	Logit	Tr. NB-II
CV sales	3.16***	0.15				
	(0.23)	(0.12)				
Range sales growth			1.15***	0.15***		
			(0.07)	(0.03)		
RMSE profits					0.41***	0.47***
					(0.08)	(0.06)
Irreversibility	6.23***	1.21***	6.30***	1.18***	5.99***	1.15***
	(0.23)	(0.09)	(0.23)	(0.09)	(0.23)	(0.10)
CV sales × Irreversibility	0.53**	-0.05				
	(0.25)	(0.13)				
Range sales growth × Irreversibility			0.15**	0.07**		
			(0.08)	(0.04)		
RMSE profits × Irreversibility					0.07	0.13**
					(0.10)	(0.07)
Sales	4.48***	1.06***	4.52***	1.09***	4.28***	1.08***
	(0.13)	(0.05)	(0.13)	(0.05)	(0.12)	(0.06)
Labour	-3.16***	-0.67***	-3.16***	-0.67***	-3.04***	-0.69***
	(0.09)	(0.04)	(0.09)	(0.04)	(0.09)	(0.04)
Capital	-0.44***	-0.02	-0.48***	-0.04***	-0.41***	-0.03
	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.02)
Productivity	-9.33***	-1.59***	-9.44***	-1.64***	-8.90***	-1.66***
	(0.33)	(0.15)	(0.32)	(0.16)	(0.30)	(0.18)
α (dispersion parameter)	no	yes	no	yes	no	yes
Industry fixed effects	yes	yes	yes	yes	yes	yes
No of obs.	36028	22187	35979	22156	30826	18987

Notes: The dependent variable is the total number of years with markups lower than unity (markdowns) at the firm level. The variables sales, labour, capital and productivity are measured as averages over time within firms. Two-step bootstrapped standard errors clustered at the plant level and stratified at the sector level are shown in parentheses (500 repetitions). *, ** and *** indicate coefficients significantly different from zero at the 10%, 5% and 1% level respectively.

As evident from the table, the coefficients on the irreversibility variable remain positive and significant in all regressions and they are in the same order of magnitude as those estimated in the main specification. This is further evidence in favour of the hypothesis that firms in industries facing more irreversible investment are more likely to incur in markdowns and to do so for a longer period of time. The coefficients on the interaction between irreversibility and the different measures of uncertainty are also generally positive and significant, with the exception of two cases in which they are not statistically different from zero (in one of these two cases, the point estimate is negative). Thus, even bearing in mind these exceptions, the evidence tends to favourour hypothesis that the effect of irreversibility on markdowns is magnified by uncertainty. Looking at the coefficients on all the other regressors, these different specifications do not affect the results qualitatively. In particular, all three alternative measures of the dispersion of sales and profits exhibit positive coefficients and are statically different from zero, both in the logit and truncated NB-II regressions.

Table 6: Markdowns and irreversibility: robustness checks

	Irreversibility avg		Depreciation		Regressors at t=1	
	Logit	Tr. NB-II	Logit	Tr. NB-II	Logit	Tr. NB-II
RMSE sales	2.90***	0.64***	4.07***	0.64***	2.71***	0.42***
	(0.22)	(0.09)	(0.40)	(0.19)	(0.27)	(0.12)
Irreversibility avg	5.46***	0.98***				
	(0.24)	(0.10)				
Depreciation			-17.21***	-3.70**		
			(2.34)	(1.57)		
Irreversibility					4.15***	0.79***
					(0.20)	(0.08)
RMSE sales × Irreversibility avg	0.28	-0.07				
	(0.33)	(0.12)				
RMSE sales × Depreciation			-9.30***	-0.41		
			(3.32)	(1.67)		
RMSE sales × Irreversibility					1.00***	0.35***
					(0.36)	(0.14)
Sales	4.34***	1.06***	4.44***	1.09***	2.81***	0.59***
	(0.13)	(0.06)	(0.14)	(0.06)	(0.07)	(0.04)
Labour	-3.06***	-0.68***	-3.14***	-0.69***	-1.88***	-0.32***
	(0.09)	(0.04)	(0.10)	(0.04)	(0.05)	(0.03)
Capital	-0.44***	-0.03*	-0.46***	-0.04**	-0.26***	-0.01
	(0.03)	(0.02)	(0.04)	(0.02)	(0.02)	(0.01)
Productivity	-8.91***	-1.59***	-8.94***	-1.64***	-5.62***	-0.89***
	(0.33)	(0.18)	(0.33)	(0.18)	(0.17)	(0.10)
α (dispersion parameter)	no	yes	no	yes	no	yes
Industry fixed effects	yes	yes	yes	yes	yes	yes
No of obs.	30470	18923	30470	18923	30457	18911

Notes: The dependent variable is the total number of years with markups lower than unity (markdowns) at the firm level. The variables sales, labour, capital and productivity are measured as averages over time within firms in the first four columns (Irreversibility avg and Depreciation) and at the beginning of the period in the last two columns (Regressors at t=1). Two-step bootstrapped standard errors clustered at the plant level and stratified at the sector level are shown in parentheses (500 repetitions). *, ** and *** indicate coefficients significantly different from zero at the 10%, 5% and 1% level respectively.

Table 6 shows additional robustness checks. The first two sets of regressions (first four columns) use two alternative measures of irreversibility, both based on the depreciation rate as in the main regressions, but here calculated as an average over the period 1990-2007 rather than at the beginning of the period. The first measure is a dummy set to unity if the depreciation rate at the three-digit industry level is lower than the median value, where the values are calculated as averages over the whole period (Irreversibility avg). On the other hand, the second measure uses directly the average depreciation rate by industry (Depreciation). As firms face more irreversible investment in industries with lower depreciation rates, the sign of the coefficients on this variable is expected to be negative. The last set of regressions (last two columns) replaces the average values of sales, labour, capital stock and productivity with their values in the first year in which each firm is surveyed (Regressors at t=1), thus minimising potential endogeneity issues.

As in all previous specifications, the measure of irreversibility has a positive effect on firms' likelihood of exhibiting a markdown in any given year as well as on the number of markdowns. The effect is statistically significant in all specifications. The effect of the interaction between irreversibility and the preferred measure of uncertainty, RMSE sales, are also generally positive, with one exception that is however not significant.[6] Thus, these specifications confirm that firms in industries with larger investment irreversibility are more likely to exhibit markdowns and that this effect may be enhanced by the presence of uncertainty. Moreover, these alternative specifications do not affect qualitatively the coefficients on the other regressors.

4. Conclusion

Recent papers estimating markups and looking at their determinants have left aside the issue of the high incidence of observations with markups lower than unity. A large proportion of firms stay in the market for many years even if they incur in losses. Setting measurement issues aside, not only is this interesting per se given that it is at odds with standard economic theory, but understanding the circumstances in which market selection may not be working fully is also important to study the aggregate dynamics of productivity and, hence, growth.

Using a large sample of French manufacturing firms for the period 1990-2007, this paper firstly estimates markups at the firm level and then documents the extent to which firms exhibit what we call markdowns, i.e. prices lower than the marginal cost, as opposed to markups. The main contribution of this paper is to provide an explanation for these negative price-cost margins using the option value approach to investment decisions. Firms facing higher investment irreversibility tend to continue operating even when prices fall below marginal costs and this effect is magnified in the presence of uncertainty.

At first glance, the fact that firms stay in the market while incurring losses for several years seems odd. Yet, our findings rationalise such behaviour based on the idea that firms wait for market conditions to improve. On the other hand, the findings do not shed any light on whether this strategy pays off (the actual "value of waiting"), for instance by affecting the long-term behaviour of firms and their survival probability. This represents an interesting avenue for future research.

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[6] The sign of the coefficients on the variables Depreciation and Depreciation interacted with RMSE sales is always negative, but as mentioned previously this is to be interpreted as a positive effect.

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