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Testing Uncertainty's Effect in Real Options with Multiple Capital Goods

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The irreversible investment theory with heterogeneous capital predicts a negative relationship between uncertainty and the investment extensive margin. We empirically explore this prediction using plant-level data for investment across multiple fixed assets, and employ a discrete ordered choice model. Our results indicate that uncertainty, even after controlling for financial constraints, induces a negative effect on the extensive margin, thereby decreasing the likelihood of investment triggering in more types of capital. This effect takes the form of both a higher probability of investment inactivity but also a lower probability of investment triggering in a higher number of capital types.

INTRODUCTION

Previous theoretical literature has established that irreversibility of capital creates an embedded call option in investment decisions that leads to a modification of the standard net present value (NPV) rule or the q-theory (McDonald and Siegel 1986; Pindyck 1988; Dixit and Pindyck 1994).[1] In particular, in ambivalent environments, investment is triggered at a higher threshold compared to the simple NPV case. Similarly, positive investment becomes optimal after exceeding a multiple of q, the size of which is known as irreversibility premium (see Chirinko and Schaller 2002). Hence decision-makers may find inactivity as being optimal in certain situations until uncertainty is partly resolved (more information is revealed), known as a 'wait-and-see' strategy. Along similar lines, Abel and Eberly (1994, 1996) have shown that irreversibility and fixed adjustment costs lead to a non-continuous investment policy that includes an inaction zone.

Moreover, like in standard financial option contracts, the option of waiting becomes more valuable as uncertainty increases. In the business fixed investment literature terminology, increased uncertainty raises the investment trigger threshold thereby extending the inaction zone. Thus uncertainty has a negative impact on business fixed investment spending by discouraging or postponement of investment.

The main body of the previous mentioned literature has dealt with a single capital good or treated multiple capital goods as homogeneous. Eberly (1997) spurred the literature studying the investment–uncertainty relationship with multiple (heterogeneous) capital goods. Essentially, she showed that in the presence of multiple capital goods, a firm's overall investment rate is decomposed into the extensive margins (the number of capital goods a firm invests in) and the intensive margins (the investment expenditure per type of capital good). Eberly and van Mieghem (1997) revisited the case of multifactor investment, demonstrating that the optimal investment decisions would follow a multidimensional threshold policy. However, their intuitive analysis was restricted to constant level of uncertainty, thereby producing static cross-sectional conclusions. Bloom *et al.* (2007), retaining the heterogeneous capital setup but allowing for time-varying uncertainty, illustrated that the response of investment to demand shocks tends to be convex, as larger (smaller) shocks induce firms to invest in more (fewer) types of capital and at more (fewer) production units. Among other conclusions, they show that variations in uncertainty are mapped to variations in both the extensive and intensive margins, which moreover reinforce one another with any supermodularity in the production process.[2]

Thus the main prediction of Eberly and van Mieghem (1997) and Bloom *et al.* (2007) is that higher uncertainty reduces the extensive margin. Let us provide some more intuition about the underlying mechanism. A core assumption is that capital goods are heterogeneous, at least in terms of their underlying degrees of irreversibility. This gives rise to type-of-capital specific trigger thresholds above which positive investment is optimal for each type. Then if one considers an ordering of the type-specific trigger thresholds, the number of capital types for which positive investment is optimal is given by the number of capital types exceeding their own trigger threshold. For instance, one may consider extremely large levels of uncertainty (that make the option of waiting very valuable) resulting in no capital good exceeding its own trigger threshold. The other extreme would be a situation where uncertainty is so low that the option value of waiting for every type of capital good is nullified, and consequently all capital goods exceed their own threshold. Between these two extremes, it becomes apparent that as uncertainty increases (decreases), the likelihood of more capital types exceeding their own threshold decreases (increases), thus producing the negative impact of uncertainty on the extensive margin.

The present paper's main contribution is that it directly confronts the hypothesis that higher uncertainty exerts a negative impact on the extensive margin with actual data. Essentially, the subsequent econometric analysis employs a large panel dataset on plant-level investment decisions for various capital goods. The richness of the dataset is vital, for it avoids, to some extent, two of the main aggregation biases that usually hamper empirical analyses.[3] First, using plant-level information overcomes the spatial aggregation (i.e. over production units) problem that results when investment decisions are observed at a higher aggregation level such as the firm. Second, observing decisions across various capital types reduces the bias that results when one considers overall investment decisions (i.e. over types of capital). Thus utilizing plant-level data by type of capital makes it more likely that zeros (investment inaction) will be observed, and in that way permits testing some of the irreversible investment literature's predictions. Furthermore, the extant literature has shown that the negative effect of uncertainty on investment is also compatible with financial constraints. To tackle this eventuality we also construct an empirical model where uncertainty is allowed to exert its effect via either financial constraints or irreversibility, and also their interplay.

The estimation of model parameters is based on a (random-effects) ordered probit, which is the ideal generating process for two reasons. First, it takes into account the discrete and non-negative nature of the extensive margin. Second, contrary to other processes (such as the Poisson), the ordered probit is more appropriate given that investment trigger thresholds are latent. Hence the ordered probit model allows the investigation of uncertainty's effects on investment inactivity but also on the decision to invest on more capital types, given that the decision-maker has cleared the inaction zone.

Uncertainty is proxied by three alternative metrics: (i) plant-specific, (ii) industry-wide and (iii) stock-market-based. All three are conditional, with the first two generated by pooled panel GARCH models (Cermeno and Grier 2006), while the third is constructed from time series GARCH models, using non-overlapping daily returns of appropriate stock market indices (Engle 1982; Bollerslev 1986).

The remainder of the paper is as follows. Section I presents the dataset utilized and the construction of variables. Section II discusses the adopted econometric methodology. Section III provides the empirical results, and Section IV concludes.

I. Data Issues

The analysis is based on plant-level data from the Annual Industrial Survey (AIS) for Greece, provided by the National Statistical Service of Greece. The dataset corresponds to 13 AISs spanning the period 1993 to 2005, and includes 6119 plants belonging to firms with more than 10 employees, across 21 manufacturing industries, giving a total sample of 57,531 plant-year observations.[4]

In Table 1, the distribution of plants by employment level is given across time. The typical cross-sectional distribution is unimodal with a peak at the 11–25 employment bracket, while plants with 51–100 and more than 100 employees account for the smallest share of plants, with about 10% of the sample distribution each. The employment bracket 0–10 accounted for the second largest concentration of plants for the period 1993–2000, while this was reversed in the 2001–05 period, with the bracket 26–50 accounting for the second largest concentration of plants.

Definition and construction of variables

Extensive margin The AIS provides (gross) values for acquisitions (AQ) and disposals (DIS) by plant for the following five fixed asset types: (i) Land, (ii) Buildings, (iii) Machinery and Equipment, (iv) Motors and Vehicles, and (v) Furniture.[5] The analysis ignores Land since investment in Land denotes a change in the number of production units (see Bloom *et al*. 2007) and would blur the measurement of extensive margin if included. Similarly, investment in Furniture is ignored for it does not relate directly to the production process. We construct gross investment as the difference between acquisitions and disposals:[6]

$$I_{i,t,K} = AQ_{i,t,K} - DIS_{i,t,K}, \tag{1}$$

Table 1

Percentage of Plants by Employment Level and Year

	Total number of employees				
Year	Less than 10	11–25	26–50	51–100	More than 100
1993	21.10	43.00	18.40	8.80	8.70
1994	24.00	40.50	42.30	8.60	8.60
1995	25.90	38.80	17.90	8.90	8.50
1996	28.10	37.20	17.10	8.90	8.60
1997	28.70	36.30	17.30	8.70	9.00
1998	28.00	35.70	18.30	8.80	9.20
1999	27.90	34.70	18.40	9.10	9.90
2000	27.90	33.10	18.80	9.70	10.50
2001	9.60	40.40	23.90	12.80	13.20
2002	8.90	40.80	24.40	12.50	13.50
2003	10.00	39.40	23.50	13.60	13.50
2004	9.90	38.20	23.90	13.80	14.30
2005	10.80	38.40	23.60	13.30	14.00
All years	21.50	38.20	19.80	10.20	10.40

Note: Numbers denote the percentage of plants in a given year within the specified employment bracket.

where K identifies each of the three asset types (Buildings B, Machinery and Equipment ME, and Motors and Vehicles V).

Then for each plant-year observation, the following dummies are created:

$$I_{i,t,B} = \begin{cases} 1 \text{ if gross investment in Buildings} > 0, \\ 0 \text{ if gross investment in Buildings} = 0, \end{cases} \tag{2}$$

$$I_{i,t,ME} = \begin{cases} 1 \text{ if gross investment in Machinery and Equipment} > 0, \\ 0 \text{ if gross investment in Machinery and Equipment} = 0, \end{cases} \tag{3}$$

$$I_{i,t,V} = \begin{cases} 1 \text{ if gross investment in Motors and Vehicles} > 0, \\ 0 \text{ if gross investment in Motors and Vehicles} = 0. \end{cases} \tag{4}$$

The extensive margin $M_{i,t}$ is defined as the count of capital types for which plant i has positive gross investment expenditure in a given time period t:

$$M_{i,t} = I_{i,t,B} + I_{i,t,ME} + I_{i,t,V}. \tag{5}$$

Table 2 summarizes the distribution of the extensive margin (across all plants) over time. The extensive margin exhibits substantial variation in the sample period under consideration, and in a typical year the percentage of plants investing in a given number of asset types drops as the latter increases. Note the considerable number of plants, almost 38% on average, with no investment in any of the asset types whatsoever (extensive margin equal to zero). Similar evidence has been reported in Caballero *et al.* (1995), Barnett and Sakellaris (1999), Doms and Dunne (1998), Gelos and Isgut (2001), Nilsen and Schiantarelli (2003), and Sakellaris (2004).

Uncertainty metrics Any econometric study focusing on investment decisions under uncertainty is severely hampered by the unobserved nature of uncertainty. This creates

TABLE 2

DISTRIBUTION OF EXTENSIVE MARGIN

Investment triggered in:	No capital goods ($M_{i,t} = 0$)	1 capital good ($M_{i,t} = 1$)	2 capital goods ($M_{i,t} = 2$)	3 capital goods ($M_{i,t} = 3$)
1993	45.86	31.59	21.24	1.31
1994	44.14	32.19	22.21	1.46
1995	40.88	34.38	23.52	1.23
1996	41.47	36.24	20.97	1.32
1997	43.36	31.73	23.94	0.97
1998	42.12	32.92	24.90	1.06
1999	39.59	33.96	25.65	0.80
2000	38.27	36.65	24.23	0.85
2001	30.95	34.42	33.17	1.47
2002	31.03	34.10	33.26	1.62
2003	30.71	33.82	34.12	1.34
2004	29.21	38.68	30.89	1.22
2005	28.16	35.53	34.94	1.37
All years	37.82	34.37	26.60	1.21

Note: Numbers denote the percentage of plants in a given year with the specified extensive margin.

two main complications. First, there is no consensus about the right source of uncertainty relevant for investment decisions. Second, assuming that a particular source is selected, one still has to make a modelling choice for generating uncertainty. On a disaggregate level, uncertainty has been considered as stemming from demand, product input prices, profits or sales (e.g. Ghosal and Loungani 1996; Peeters 1999; Cassimon *et al.* 2004; Fedderke 2004; Drakos and Goulas 2006). Another approach is to base uncertainty measures on stock return volatility (e.g. Leahy and Whited 1996; Bulan 2005; Bloom *et al.* 2007). Finally, a number of studies have resorted to survey-based measures of uncertainty where entrepreneurs or analysts are asked to state the level of perceived uncertainty (e.g. Patillo 1998; Guiso and Parigi 1999; Bond and Cummins 2004; Le *et al.* 2004; Drakos 2006; Driver *et al.* 2006). The second complication is typically dealt with either by constructing unconditional measures, such as the sample standard deviation of the uncertainty capturing variable, or by conditional measures generated from GARCH models.

In the present paper we opt for conditional measures, which have the distinct advantage of reflecting the information available at the time of decision-making. Moreover, because the unit of analysis is the plant, we primarily resort to plant-specific conditional uncertainty stemming from revenue. However, a metric based on plant revenues may conflate uncertainty with other factors, and especially measurement error. A possible solution is to employ a metric of uncertainty that is independently measured from any of the other explanatory variables. To this end we follow two alternative routes. First, we construct industry-level uncertainty that does not suffer from plant idiosyncrasies. Of course, this measure is still subject to the measurement error mentioned earlier, albeit to a far lesser extent. Second, we use an industry uncertainty proxy, calculated from publicly quoted firms in the relevant industry. This metric clearly eliminates the feedback from measurement errors in own revenue since it uses extraneous information. Of course, one should bear in mind that stock return volatilities may be subject to other deficiencies.[7]

Thus we begin by constructing plant-specific uncertainty $\hat{\sigma}_{i,t} = \sqrt{\hat{\sigma}^2_{i,t}}$, estimating a pooled panel GARCH (PP-GARCH hereafter) model for the conditional volatility of total revenue as a ratio to value added R. The following autoregressive model is employed:

$$R_{i,t} = \theta_0 + \theta_1 R_{i,t-1} + u_{i,t}, \tag{6}$$

where the θ terms stand for estimable parameters, and $u_{i,t}$ is a disturbance term.

In particular, assuming that $u_{i,t} \sim N[0, \Omega_{i,t}]$—i.e. the $u_{i,t}$ are multivariate normal error terms with a time-varying conditional variance–covariance matrix—produces a PP-GARCH model (Cermeno and Grier 2006). The variance–covariance matrix $\Omega_{i,t}$ is time-dependent, with its diagonal and off-diagonal elements given by the following equations:

$$\sigma^2_{i,t} = \phi_0 + \sum_{n=1}^{p} \phi_n \sigma^2_{i,t-n} + \sum_{m=1}^{q} \eta_m u^2_{i,t-m}, \quad \text{for} \quad i = 1, \ldots, I, \tag{7}$$

$$\sigma_{i,j,t} = \psi_0 + \sum_{n=1}^{p} \psi_n \sigma_{i,j,t-n} + \sum_{m=1}^{q} \rho_m u_{i,t-m} u_{j,t-m}, \quad \text{for } i \neq j, \tag{8}$$

where the ϕ, ψ, η, ρ terms denote unknown constant parameters to be estimated.

Although multivariate GARCH models are also available, they are not practical for most panel applications because they require the estimation of a large number of parameters, which consumes degrees of freedom rapidly. In contrast, PP-GARCH estimation, by imposing common dynamics on the variance–covariance process across cross-sectional units, reduces the number of parameters dramatically, ensuring parsimony. Furthermore, the PP-GARCH model does not imply constant cross-sectional correlation over time.

We calculate annual total revenue as a ratio to value added on an industry level, and follow a similar procedure to generate industry-wide conditional uncertainty $\hat{\sigma}_{ind,t}$, where *ind* identifies the industry. This provides us with 21 time-varying industry-specific uncertainty measures.

Finally, we apply standard time series GARCH models (Engle 1982; Bollerslev 1986) to generate the annual conditional volatility for daily non-overlapping returns of industrial indices trading in the Athens Stock Exchange: $\hat{\sigma}_{sm,t}$, where *sm* identifies the relevant stock market industrial index. A complete matching of the main (plant-level) sample with stock market indices was not possible. This was due to the traded indices not corresponding exactly to NACE codes, and because when correspondence was possible, the stock market indices did not trade for the whole sample period. This incomplete matching left us with six industries, namely (i) Food and Beverages, (ii) Textiles, (iii) Printing and Publishing, (iv) Petroleum and Coal Products, (v) Non-metallic Minerals, and (vi) Basic Metals, for which data are available from 2001 onwards. Although this severely reduces the working sample, we choose to construct a stock-market-based uncertainty as a means of conducting sensitivity analysis.

Panel A of Table 3 reports the estimation results for the PP-GARCH(1,1) for plant-specific and industry-wide uncertainties, while Panel B reports the time series GARCH

TABLE 3
ESTIMATING UNCERTAINTY PROXIES

Panel A: pooled panel GARCH[a]

Regressor[b]	Plant-specific	Industry-wide
AR-1	0.841***	0.703***
AR-2	—	0.253***
σ^2_{t-1}	0.772***	0.730***
u^2_{t-1}	0.428***	0.175***

Panel B: time series GARCH (stock-market-based)[c]

	Food and Beverages	Textiles	Printing and Publishing	Petroleum and Coal Products	Non-metallic Minerals	Basic Metals
AR-1	0.137***	0.068***	0.107***	0.034	0.088***	0.190***
σ^2_{t-1}	0.075***	0.110***	0.137***	0.058***	0.143***	0.112***
u^2_{t-1}	0.915***	0.831***	0.836***	0.879***	0.783***	0.808***

Notes
[a]Dependent variable is the ratio of total revenue to value added.
[b]AR-1, AR-2 denote the first- and second-order lags, respectively, of the relevant dependent variable, while the remaining terms denote the GARCH part of the model.
[c]Dependent variable is the daily non-overlapping return of the corresponding stock market index.
***Indicates statistical significance at the 1% level.
Intercepts are not reported, for brevity.

results for daily non-overlapping returns for each of the six stock market industrial indices.[8] The coefficients in the conditional variance equations are highly significant and suggest persistence in volatility, consistent with volatility clustering. Then the fitted values from the volatility equation are recovered and used as proxies for uncertainty.

Control variables The reduced-form models that will follow in order to explore the potential impact of uncertainty on the extensive margin—apart from a set of zero/one industry and year dummies when applicable—will also condition on a set of covariates capturing important plant-specific characteristics defined as follows: SL is the ratio of sales to value added, CF is the ratio of cash flow (gross operating profit) to value added, EQ is the ratio of equity to value added, LO is the ratio of bank loans to value added, and finally EMP is the logarithm of the number of employees.[9]

II. Econometric Methodology

As discussed earlier, the basic prediction of the real options theory is that uncertainty, through the value of the embedded call option, leads to a deferral of investment decisions. In other words, it directly influences the agents' choice regarding triggering investment, by raising the relevant threshold. The analysis deals with the real option theory's predictions taking into account all capital goods, and essentially assesses the impact of uncertainty on the extensive margin.

Extensive margin and uncertainty

Expanding the analysis to multiple capital types, the plant has now to decide on how many types of capital to trigger positive investment among the available types of fixed assets. Recall that the extensive margin $M_{i,t}$ is defined as the count of capital types for which plant i has positive gross investment expenditure in a given time period t.

We model $M_{i,t}$ as being generated by a continuous process that, when crossing a threshold, leads to positive investment in a given type of capital good. Crossing further thresholds leads to investment in additional types of capital goods. The starting point for the empirical specification is an underlying latent variable $M^*_{i,t}$ for each plant i at year t, which is a (linear in parameters) function of a vector of observed characteristics $\mathbf{x}_{i,t}$, with unknown weights $\boldsymbol{\gamma}$ and a random error term $\varepsilon_{i,t}$. The set of $\mathbf{x}_{i,t}$ includes the control variables $SL_{i,t-1}$, $CF_{i,t-1}$, $EMP_{i,t}$, $EQ_{i,t-1}$, $LO_{i,t-1}$ and $\sigma_{i,t}$.[10]

This latent variable represents a tendency to change mechanism as follows (see Wooldridge 2002):

$$(9) \qquad M^*_{i,t} = \mathbf{x}'_{i,t}\boldsymbol{\gamma} + \varepsilon_{i,t}.$$

Given the panel dimension of the sample (repeated observations over time for plants), one may condition on plant heterogeneity by augmenting equation (9) by an unobserved effect δ_i, treated as random, assuming that $E(\mathbf{x}'_{i,t}\delta_i) = 0$ for all i,t, leading to

$$(10) \qquad M^*_{i,t} = \mathbf{x}'_{i,t}\boldsymbol{\gamma} + \delta_i + \varepsilon_{i,t}.$$

The observed discrete variable $M_{i,t}$ is generated from the unobserved $M^*_{i,t}$ in the following way:

$$(11) \qquad M_{i,t} = m \quad \text{if } \alpha^*_m < M^*_{i,t} \leq \alpha^*_{m+1},$$

with $m = 0, 1, 2, 3$, while $\alpha_0^* = -\infty$ and $\alpha_{K+1}^* = +\infty$. If one lets $\Phi_\varepsilon(\bullet)$ denote the cumulative distribution function of ε, then it follows that

$$\begin{aligned} p_{i,t,m} &= \Pr[M_{i,t} = m|\mathbf{x}_{i,t}] \\ &= \Pr[\alpha_m^* < M_{i,t}^* \leq \alpha_{m+1}^*] \\ &= \Pr[\alpha_m^* - \mathbf{x}'_{i,t}\gamma < \varepsilon_{i,t} \leq \alpha_{m+1}^* - \mathbf{x}'_{i,t}\gamma] \\ &= \Phi_\varepsilon(\alpha_m^* - \mathbf{x}'_{i,t}\gamma) - \Phi_\varepsilon(\alpha_{m+1}^* - \mathbf{x}'_{i,t}\gamma). \end{aligned} \tag{12}$$

Thus the extensive margin is modelled by a random-effects ordered probit, and the parameters of interest are estimated by maximum likelihood, further assuming that $E(\mathbf{x}'_{i,t}\boldsymbol{\varepsilon}_{i,t}) = 0$.

The impact of uncertainty can be explored by allowing it to be part of the **x** vector. In general, a negative value for an estimated coefficient in ordered probability models implies that an increase in the corresponding variable will unambiguously decrease the probability of the highest-ordered discrete category being selected, and clearly increase the probability of the lowest-ordered discrete category being selected. The estimated coefficients, however, do not provide a clear indication of how changes in a given covariate affect the probabilities of intermediate-ordered categories. Instead, marginal probability effects can be computed for each category to assess each variable's impact on the probability for each category threshold.[11] In particular, measuring uncertainty's impact on the extensive margin can be accommodated by estimating its marginal effects, which correspond to the derivative of the density function with respect to uncertainty, $\partial p_{i,t,m}/\partial\sigma$.

III. Empirical Results

Three alternative specifications have been estimated, denoted as Model 1 (plant-specific uncertainty), Model 2 (industry-wide uncertainty) and Model 3 (stock-market-based uncertainty).[12] For Models 1 and 2, estimation was based on an unbalanced panel of 6032 plants from 1994 to 2005, giving a total of 47,213 observations, while for Model 3 the number of plants was 1643 covering the period 2001–05, providing us with 6524 observations.[13] For all three models, the potential effect of uncertainty on the extensive margin was explored using an ordered probit model, allowing for random effects, and results are given in Table 4.[14]

Across all three specifications, the coefficient of uncertainty is found to be significantly negative, a finding which is compatible with the prediction of the real options theory. The negative effect of uncertainty on investment has been documented by a large number of previous econometric studies (e.g. Pindyck and Solimano 1993; Ghosal and Loungani 1996, 2000; Leahy and Whited 1996; Guiso and Parigi 1999; Bulan 2005; Bloom *et al.* 2007).

The calculation of marginal probability effects, reported in Table 5, allows us to shed light on the manner in which uncertainty affects the extensive margin. In particular, a common feature across specifications is that uncertainty exerts a large impact on the probability that the extensive margin is zero, highlighting the underlying deferral mechanism. In other words, higher uncertainty increases the likelihood of investment inactivity on all types of capital. Based on Model 1, the probability that the average plant does not trigger investment in any of the three capital types (zero extensive margin) is

TABLE 4
RANDOM EFFECTS ORDERED PROBIT MODEL FOR EXTENSIVE MARGIN

	Estimated coefficient (standard error)		
Covariate[a]	Model 1	Model 2	Model 3
σ	– 0.173***	– 0.064*	– 0.307***
	(0.012)	(0.038)	(0.05)
$SL_{i,t-1}$	0.078***	0.032**	0.051
	(0.013)	(0.013)	(0.035)
$CF_{i,t-1}$	0.125***	0.127***	0.157***
	(0.010)	(0.010)	(0.034)
$EMP_{i,t}$	0.044***	0.172***	0.616***
	(0.08)	(0.04)	(0.029)
$EQ_{i,t-1}$	0.067***	0.023***	0.101***
	(0.05)	(0.004)	(0.013)
$LO_{i,t-1}$	0.168***	0.141***	0.257***
	(0.026)	(0.025)	(0.061)
Sigma[b]	0.909***	0.906***	0.913***
	(0.012)	(0.012)	(0.028)
Log-likelihood	– 43,742.17	– 44,543.15	– 6385.44
Restricted log-likelihood	– 48,287.11	– 51,123.46	– 6943.13
Wald test	9089.87***	13,160.62***	1115.39***
Pseudo R-squared[c]	0.094	0.128	0.080
% of correct predictions	0.47	0.35	0.48
Observations	47,213	47,213	6524

Notes
[a]Model 1 uses plant-specific uncertainty $\sigma_{i,t}$; Model 2 uses industry-wide uncertainty $\sigma_{ind,t}$; Model 3 employs stock-market-based uncertainty $\sigma_{sm,t}$.
[b]Significant values of sigma denote significance of the random-effect.
[c]Corresponds to McFadden's measure.
***,**,*Indicate statistical significance at the 1%, 5%, 10% levels.

raised by approximately 4.8 percentage points due to a unit increase in plant-specific uncertainty. Based on Model 2, industry-wide uncertainty raises the probability of zero extensive margin by 1.6 percentage points, while in Model 3 stock-market-based uncertainty increases the likelihood of investment inactivity by 1.4 percentage points.[15]

As it relates to the probabilities of observing non-zero extensive margins, uncertainty exerts a negative impact whose absolute magnitude follows an inverted U-shape. This finding is common across all three specifications. In particular, for the case of a unit increase in plant-specific uncertainty, the likelihoods that the extensive margin is equal to one, two or three are reduced by 0.7, 3.8 and 0.2 percentage points.

All in all, conditional uncertainty is found to induce a significantly negative effect on the extensive margin, suggesting that higher uncertainty decreases the likelihood that a plant will trigger investment in more types of capital. This negative effect takes the form both of a higher probability of investment inactivity but also of a lower probability of investment triggering in a higher number of capital types. The finding concerning inactivity is in line with the predictions of the real options theory, which advocates that higher uncertainty results in investment deferral. Moreover, the strong relationship between the extensive margin and uncertainty also highlights the important role of

TABLE 5
MARGINAL PROBABILITY EFFECTS

	Model 1	Model 2	Model 3
$\frac{\partial(\Pr[M_{i,t}=0\vert\mathbf{x}_{i,t}])}{\partial\sigma}$	4.82%	1.64%	7.55%
$\frac{\partial(\Pr[M_{i,t}=1\vert\mathbf{x}_{i,t}])}{\partial\sigma}$	– 0.72%	– 0.12%	0.89%
$\frac{\partial(\Pr[M_{i,t}=2\vert\mathbf{x}_{i,t}])}{\partial\sigma}$	– 3.81%	– 1.36%	– 7.80%
$\frac{\partial(\Pr[M_{i,t}=3\vert\mathbf{x}_{i,t}])}{\partial\sigma}$	– 0.29%	– 0.17%	– 0.65%

Notes
Model 1 uses plant-specific uncertainty $\sigma_{i,t}$; Model 2 uses industry-wide uncertainty $\sigma_{ind,t}$; Model 3 employs stock-market-based uncertainty $\sigma_{sm,t}$.
The marginal effects sum to zero by default. Differences are due to rounding errors.

capital heterogeneity, taking the form of capital type-specific trigger thresholds. Thus the reported findings provide direct empirical support to the theoretical predictions of Eberly and van Mieghem (1997) and Bloom *et al.* (2007).

The role of financial constraints[16]

The previously conducted econometric analysis attributed the effect of uncertainty solely to irreversibility. However, a negative impact of uncertainty on investment is also compatible with the presence of financial constraints, which can be viewed as another source of friction. In particular, investment inactivity can be generated by either of the two frictions individually (financial constraints or irreversibility) and also by their potential interplay. Thus any empirical model, like the one presented earlier, that does not explicitly control for both frictions is insufficient in terms of ascribing inactivity to a particular cause (friction) and also misleading, in relation to the magnitudes of estimated effects (Holt 2003). In fact, Holt (2003) shows that if both frictions are in operation (both constraints binding), then the juxtaposition of irreversibility and financial constraints produces a higher impact on investment than either constraint individually. In a similar line of reasoning, Caggese (2007) shows that irreversibility and financial constraints interact and reinforce each other, resulting in an amplification of individual effects on investment behaviour. Thus as a starting point one needs two metrics, based on which plants can be classified as having higher likelihood of being financially constrained and as having higher likelihood of facing irreversible investment decisions.

Plant size, measured by the total number of employees, is used as an indicator for financial constraints. Size has been used as an attribute by several theoretical and empirical studies, based on the core argument that information-based financial constraints are more likely to have a greater impact on small firms, partly because they tend to be more 'immature', and have fewer seizable assets that obstruct access to capital (e.g. Gertler 1988; Hu and Schiantarelli 1994; Gilchrist and Himmelberg 1998; Audretsch and Elston 2002). For the Greek case specifically, there has been reported evidence in favour of financial constraints (Drakos and Kallandranis 2005a, b).

To investigate the effect of financial constraints on the extensive margin, each year plants are divided into small ($SMALL_{i,t}$) and large ($LARGE_{i,t}$) based on whether their employment level is below or above the median of the cross-sectional distribution, respectively. A distinct advantage of splitting plants in such a manner is that it is flexible enough to allow plants moving states from year to year (i.e. a plant could be classified as constrained in one year while unconstrained in another).

As a proxy for the degree of irreversibility that plants face, we adopt a transactions-based view, where irreversibility is a friction regarding the decision-maker's ability to undo capital commitments *per se*, and takes the form of a price differential between buying (p^+) and selling (p^-) prices for capital (Abel and Eberly 1996; Chirinko and Schaller 2002). Basically, the degree of irreversibility (or sunkness) of capital is a function of the price ratio (or differential). For instance, full irreversibility would be denoted by a situation where $p^+ > 0$ and $p^- = 0$, resulting in $\lim_{p^- \to 0}(p^+/p^-) \to +\infty$.

In the same manner, full reversibility would be denoted by $p^+ = p^- > 0$ and $(p^+/p^-) = 1$. Finally, intermediate cases of (partial) irreversibility would be expressed by $p^+ > p^- > 0$ and $(p^+/p^-) > 1$.

However, although buying prices maybe observable in empirical applications, this is not in general true for selling prices. In order to overcome this unobservability, the literature has proposed leasing penetration as an indirect observable indicator that may reflect the degree of irreversibility in an industry. In particular, the share of sunk outlays ('sunkness') is likely to be low when capital can be easily leased (Kessides 1990). In other words, the intensity of the rental market in the industry could be viewed as a proxy for the mobility and fungibility of the capital. Kessides goes even further, stating that the intensity of the rental market may be viewed as an indicator of the capital's specificity. If the capital employed is mostly firm-specific, or very expensive to relocate, then it is unlikely that an active rental market at the industry level would exist. Hence for each year we construct the share of leasing expenditures over the sum of leasing expenditures and acquisitions at the industry level. Then, based on the median of the cross-sectional distribution, we classify each plant as facing higher irreversibility ($HIRR_{i,t}$) if it operates in an industry with leasing penetration below the median, and lower irreversibility otherwise ($LIRR_{i,t}$).

As a prelude to our econometric analysis, we report in Table 6 the percentage of zero investment episodes (inactivity) by type of capital across plants with assumed different degrees of financial constraints and irreversibility. The emerging picture is indicative of a higher propensity of investment inactivity for plants with a higher likelihood of binding financial and irreversibility constraints. Moreover, this holds true for each type of capital as well as for total investment. In Panel B of the same table, the distribution of the extensive margin across the two groups is also provided. It turns out that the presence of the two frictions is crucial for the extensive margin, since we observe that constrained plants exhibit higher inactivity (zero extensive margin), and lower propensities of investment triggering in more types of capital (any other non-zero extensive margin). Thus, based on this information, considering a dependence of the extensive margin on the two frictions seems a fruitful exploration.

Given that our aim is to disentangle the effects of the financial constraints and irreversibility effects, as well as investigate their interplay on the extensive margin, we proceed as follows. We define three dummies that essentially partition the sample into four mutually exclusive segments:

$$D_{FC} = \begin{cases} 1 \text{ if } SMALL_{i,t} \wedge LIRR_{i,t}, \\ 0 \text{ otherwise,} \end{cases}$$

TABLE 6
ZERO INVESTMENT EPISODES AND EXTENSIVE MARGIN BY CAPITAL TYPE AND FRICTION

Panel A: Zero investment episodes by capital type

	Small plants	Large plants	Higher irreversibility	Lower irreversibility	Small plants and higher irreversibility	Large plants and lower irreversibility
Buildings	81.78%	49.57%	72.13%	65.07%	84.31%	46.76%
Machinery	50.58%	19.38%	40.64%	34.85%	53.54%	18.22%
Vehicles	90.57%	74.58%	85.93%	82.15%	91.91%	73.00%
Total investment	45.91%	16.15%	36.86%	30.57%	49.15%	14.73%

Panel B: extensive margin

	Small plants	Large plants	Higher irreversibility	Lower irreversibility	Small plants and higher irreversibility	Large plants and lower irreversibility
$M_{i,t}=0$	50.77%	20.14%	41.36%	35.03%	53.81%	18.53%
$M_{i,t}=1$	34.26%	34.52%	34.63%	34.16%	33.71%	33.46%
$M_{i,t}=2$	14.38%	43.30%	22.99%	29.43%	12.04%	45.85%
$M_{i,t}=3$	0.59%	2.05%	1.02%	1.36%	0.44%	2.15%

Note: Numbers denote the percentage of plants.

identifying plants considered as financially constrained only,

$$D_{IRR} = \begin{cases} 1 \text{ if } LARGE_{i,t} \wedge HIRR_{i,t}, \\ 0 \text{ otherwise,} \end{cases}$$

identifying plants considered as facing higher irreversibility only, and

$$D_{FC,IRR} = \begin{cases} 1 \text{ if } SMALL_{i,t} \wedge HIRR_{i,t}, \\ 0 \text{ otherwise,} \end{cases}$$

identifying plants considered as financially constrained and facing higher irreversibility.

Then we re-estimate our basic model, allowing uncertainty to affect the extensive margin with varying magnitudes between (i) financially constrained and unconstrained plants, (ii) plants with higher and lower irreversibility, and (iii) plants that are both financially constrained and facing irreversibility. Thus we augment the previously employed specification with the following covariates:

$$D_{FC} \times \sigma_{i,t}, \quad D_{IRR} \times \sigma_{i,t}, \quad D_{FC,IRR} \times \sigma_{i,t}.$$

Our priors are that uncertainty's (negative) effect on the extensive margin will be higher (in absolute magnitude) for plants for which each individual friction is in operation. In addition, we expect the effect to be accentuated for plants facing both frictions. In algebraic terms, these priors can be expressed in terms of the signs and magnitudes of the marginal probability effects as follows:

$$\left(\frac{\partial p_{i,t,m}}{\partial \sigma} | D_{FC}=1\right) < 0, \quad \left(\frac{\partial p_{i,t,m}}{\partial \sigma} | D_{IRR}=1\right) < 0, \quad \left(\frac{\partial p_{i,t,m}}{\partial \sigma} | D_{FC,IRR}=1\right) < 0$$

and

$$\left|\frac{\partial p_{i,t,m}}{\partial \sigma}|D_{FC,IRR}=1\right| > \left|\frac{\partial p_{i,t,m}}{\partial \sigma}|D_{FC}=1\right|, \left|\frac{\partial p_{i,t,m}}{\partial \sigma}|D_{IRR}=1\right|.$$

Table 7 summarizes the estimation results of the random effects ordered probit model for the extensive margin. The parameters of the three interaction terms are significantly negative, suggesting that uncertainty exerts a negative impact on the extensive margin for plants facing constraints. The significance of all three parameters implies that each individual friction leads, via uncertainty, to lower investment margin, and they also have a significant joint impact.

We can further quantify these impacts by estimating the marginal probability effects, which we report in Table 8.

TABLE 7

RANDOM EFFECTS ORDERED PROBIT MODEL FOR EXTENSIVE MARGIN BASED ON BOTH FRICTIONS

	Estimated coefficient (standard error)	
Covariate[a]	Model 1	Model 3
σ	− 0.0006	− 0.320***
	(0.016)	(0.054)
σ^*D_{FC}	− 0.200***	− 0.039
	(0.015)	(0.038)
σ^*D_{IRR}	− 0.042***	− 0.091**
	(0.015)	(0.036)
$\sigma^*D_{FC,IRR}$	− 0.232***	− 0.039
	(0.017)	(0.05)
$SL_{i,t-1}$	0.077***	0.058
	(0.013)	(0.035)
$CF_{i,t-1}$	0.126***	0.156***
	(0.010)	(0.034)
$EMP_{i,t}$	0.377***	0.594***
	(0.009)	(0.038)
$EQ_{i,t-1}$	0.069***	0.102***
	(0.05)	(0.013)
$LO_{i,t-1}$	0.168***	0.263***
	(0.026)	(0.061)
Sigma[b]	0.877***	0.917***
	(0.012)	(0.028)
Log-likelihood	− 43,624.10	− 6379.51
Restricted log-likelihood	− 47,857.93	− 6913.99
Wald test	8467.65***	1068.96***
Pseudo R-squared[c]	0.088	0.077
% of correct predictions	0.48	0.47
Observations	47,213	6524

Notes

[a]Model 1 uses plant-specific uncertainty $\sigma_{i,t}$; Model 3 employs stock-market-based uncertainty $\sigma_{sm,t}$. Results for Model 2 are not reported because the process failed to converge.

[b]Significant values of sigma denote significance of the random effect.

[c]Corresponds to McFadden's measure.

***,**Indicate statistical significance at the 1%, 5% levels.

TABLE 8

MARGINAL PROBABILITY EFFECTS BASED ON BOTH FRICTIONS

	$D_{FC} = 1$	$D_{IRR} = 1$	$D_{FC,IRR} = 1$
$\dfrac{\partial(\Pr[M_{i,t} = 0 \mid \mathbf{x}_{i,t}])}{\partial\sigma}$	5.66%	1.20%	6.50%
$\dfrac{\partial(\Pr[M_{i,t} = 1 \mid \mathbf{x}_{i,t}])}{\partial\sigma}$	– 0.92%	– 0.19%	– 1.07%
$\dfrac{\partial(\Pr[M_{i,t} = 2 \mid \mathbf{x}_{i,t}])}{\partial\sigma}$	– 4.44%	– 0.94%	– 5.15%
$\dfrac{\partial(\Pr[M_{i,t} = 3 \mid \mathbf{x}_{i,t}])}{\partial\sigma}$	– 0.30%	– 0.06%	– 0.35%

Note: The marginal effects sum to zero by default. Differences are due to rounding errors.

The probability of overall investment inactivity (zero extensive margin) for financially constrained plants is 5.6 percentage points higher, while for plants facing higher irreversibility it is 1.2 percentage points higher. Hence both frictions increase the probability that a plant falls in the inaction zone. Another important finding is that plants that are subject to both constraints fall in the investment inaction region with 6.5 percentage points higher probability. Hence, according to the estimated marginal effects, financial constraints compared to irreversibility are found to affect more strongly the decision (not) to trigger investment. In addition, the likelihood that inaction is observed is highest when both constraints are in operation.

Apart from the effects on inactivity, the frictions also lead to a lower probability that plants move to any of the higher-order extensive margins. In particular, financially constrained plants trigger investment in any type of capital with 0.9 percentage points lower probability, while plants with irreversible investment do so with 0.1 percentage points lower probability. Both frictions reduce the probability of investment triggering in any capital type by 1 percentage point. The probability that investment will be initiated in any two types of capital is lower by 4.4 percentage points for financially constrained plants, and 0.9 percentage points for plants facing irreversibility, while it is 5.1 percentage points lower when plants face both constraints. Finally, the probability that investment is triggered for all three types of capital is reduced by 0.3, 0.6 and 0.3 percentage points for financially constrained, plants facing irreversibility and both frictions, respectively.

IV. CONCLUSIONS

This study is a microeconometric investigation of the empirical validity for the negative relationship between the extensive margin and uncertainty, motivated by the irreversibility literature with heterogeneous capital goods (Eberly and van Mieghem 1997; Bloom *et al.* 2007).

Utilizing longitudinal plant-level data on investment expenditures across multiple fixed assets, to avoid aggregation biases, a random effects ordered probit model was employed. The empirical specification, apart from the irreversibility channel, explicitly considered financial constraints as a further factor affecting the underlying relationship. The results support the hypothesis that uncertainty exerts a significantly negative impact on the extensive margin. In particular, financially constrained plants and plants facing higher irreversibility exhibit a higher likelihood of falling in the inaction zone. Apart from the effects on inactivity, the frictions lead to a lower probability that plants move to any of the higher-order extensive margins.

These findings lend empirical support to the theoretical predictions of the real options theory in the context of multiple assets as derived by Eberly and van Mieghem (1997) and Bloom *et al.* (2007). Furthermore, these findings provide indirect evidence for asset-specific trigger thresholds that produce a link between uncertainty and the decision regarding the number of capital goods.

Future research could utilize even more disaggregate investment, which essentially requires data on more types of capital. In addition, one could jointly model the extensive and intensive margins, in order to explore both the decisions regarding the choices of number of asset types and the level of expenditure per asset type. Finally, not only the decisions to trigger positive investment, but also the decisions to trigger negative investment should be under scrutiny. All of the above would provide a more complete picture of uncertainty's impact on overall investment.

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NOTES

1. An irreversible investment opportunity is analogous to a financial call option where the holder has the right, but not the obligation, within a specified time period to pay an exercise price and receive in return the underlying asset. Exercising ('killing') the option is irreversible in the sense that although the underlying asset maybe resold, the investor cannot retrieve the option.
2. Supermodularity of a production function suggests that increases in a given input raise the marginal product of the other inputs. In other words, the inputs are complementary or cooperant (Topkis 1978; Milgrom and Shannon 1994). Algebraically, assuming a production function with N capital inputs $F(K_1, K_2, \ldots, K_N)$, the marginal product of any individual input is increasing in the other inputs. This implies that $\partial F_K/\partial K_j > 0$ for all $i \neq j$. The Cobb–Douglas and constant elasticity of substitution (CES) production functions satisfy these properties (see Dixit 1997; Bloom *et al.* 2007).
3. The temporal aggregation bias is rather harder to surpass.
4. The industries are: (1) Food and Beverages, (2) Tobacco, (3) Textiles, (4) Clothing, (5) Leather and Footwear, (6) Wood and Cork, (7) Paper and Paper Products, (8) Printing and Publishing, (9) Petroleum and Coal Products, (10) Chemicals, (11) Rubber Articles and Plastics, (12) Non-metallic Minerals, (13) Basic Metals, (14) Manufacture of Final Metallic Products, (15) Machines and Equipment Articles, (16) Electrical Machines, Apparatus, etc., (17) Radio, TV, Communications Appliances, (18) Medical and Accuracy Instruments, (19) Transport Equipment, (20) Other Transport Equipment, and (21) Furniture and Other Industries. Data for the industries Office Accounting and Computing Machinery and Recycling were not available due to confidentiality.
5. Expenditures refer to acquisition of new assets.
6. The analysis has also considered only investment acquisitions and results were insensitive.
7. Typical problems arise due to bubbles or fads (Shiller 1981).
8. Alternative specifications of the GARCH family were considered for plant and industry uncertainties, and the preferred models were chosen using the Akaike Information Criterion (Akaike 1969).
9. Following Bond *et al.* (2003), industry and year effects are included to capture variations in the user-cost of capital for which direct information is not available. Furthermore, year effects capture overall macroeconomic-systematic effects affecting all plants. Division by value added is done for normalization purposes. Sales are included in order to proxy the investment opportunity set motivated by the Sales Accelerator model (Abel and Blanchard 1986). Cash flow is intended to capture any additional information not embodied in Sales and is motivated by the capital market imperfections literature (Fazzari *et al.* 1988). Equity and Bank Loans are proxies for financing mix and credit availability. Employment level is used as a proxy for plant size.
10. Note a caveat of the model: due to the fact that uncertainty has been estimated, it is subject to the standard 'errors-in-variables' problem.
11. Note that the sum of marginal probability effects equals zero since the sum of probabilities is constrained. Essentially, they show the obvious effect that if the probability of a given outcome is

increased, this shifting must be balanced by a decrease of equal magnitude in the sum of all other outcomes' probabilities.

12. The set of regressors also includes fixed time and industry effects.
13. Estimation starts from 1994 since conditional volatility has usable observations after 1993 due to GARCH estimation.
14. Estimation was also conducted assuming a logistic distribution, producing similar conclusions. Results are available from the author on request.
15. The coefficient of *sigma* is significantly different from zero, implying that pooling across plants would not be statistically justifiable.
16. I would like to thank an anonymous referee for pointing this out. In fact, the whole section has been motivated by the referee's insightful comments.

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