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The Hazard Rate of Foreign Direct Investment: A Structural Estimation of a Real-option Model*

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Abstract

The hazard rate of investment is derived within a real-option model, and its properties are analysed so as to directly study the relation between uncertainty and investment. Maximum likelihood estimates of the hazard are calculated using a sample of multinational enterprises (MNEs) that invested in Central and Eastern Europe over the period 1990–98. Employing a standard, non-parametric specification of the hazard, our measure of uncertainty has a negative effect on investment, but the reduced-form model is unable to control for nonlinearities in the relationship. The structural estimation of the option-based hazard is instead able to account for the nonlinearities and exhibits a significant value of waiting, although the latter is independent of our measure of uncertainty. This finding supports the existence of alternative channels through which uncertainty can affect investment.

I. Introduction

During the last decades, real-option models have become increasingly popular for understanding the impact of uncertainty and sunk costs on entry. In

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particular, the option theory of irreversible investment (Dixit and Pindyck, 1994) predicts that uncertainty raises the critical value at which it is optimal to invest. Therefore, it has been concluded that uncertainty should have a negative effect on investment and empirical evidence of these models has been provided.

More specifically, empirical studies have employed either estimates of uncertainty derived from subjective opinions of managers in structured surveys (Patillo, 1998; Guiso and Parigi, 1999) or estimates of the variance of macroeconomic variables, such as output (Driver and Moreton, 1991; Fedderke, 2004), stock prices (Leahy and Whited, 1996; Lensink, 2002), inflation (Huizinga, 1993), interest rates (Ferderer, 1993), exchange rates (Campa, 1993; Goldberg, 1993; Darby *et al.*, 1999; Serven, 2003), oil prices (Favero, Pesaran and Sharma, 1994; Hurn and Wright, 1994), copper prices (Harchaoui and Lasserre, 2001) and institutional variables (Brunetti and Weder, 1998; Altomonte, 2000; Fedderke, 2004). The general finding in these studies is that uncertainty depresses investment thereby claiming support for the real-option theory of investment.

The option effect is actually but one of three possible channels through which uncertainty can negatively affect investment, the other two being the presence of financing constraints and the firms' attitudes towards risk.[1] In particular, Ghosal and Loungani (2000) find the negative relationship between uncertainty and investment to be substantially greater in industries dominated by small firms, a result supporting the role of financing constraints rather than the option channel in explaining the investment–uncertainty relation. In fact, should the real-option argument be significant, they argue, the opposite result would have appeared in the estimations because of higher sunk costs in industries dominated by large firms.

Within the same real-option literature, however, Sarkar (2000) argues that higher volatility surrounding the underlying project value also increases the probability that the trigger value of investment will be hit. He shows that the relation between uncertainty and the probability that investment will take place within a certain period may be nonlinear, with greater uncertainty actually hastening investment for some parameter configurations.[2] Empirical studies to explicitly test these nonlinearities in the uncertainty–investment relationship are Lensink (2002) and Serven (2003). Lensink (2002) finds that the impact of uncertainty on aggregate investment differs for low and high

[1]See the references provided in Ghosal and Loungani (2000). When investment relates to capacity choice, other channels can be identified as well (Aiginger 1987; Driver and Moreton, 1991).

[2]Within the literature on (partially) irreversible investment, other explanations for a possible reverse effect of uncertainty have been put forward, most notably construction lags generating an interval of time between the investment decision and the receipt of the project's first revenues (Bar-Ilan and Strange, 1996).

values of uncertainty. Serven (2003) also finds a nonlinear result, pointing out that the negative effect of uncertainty only matters when uncertainty itself exceeds some critical level (threshold effects).

Although the empirical findings cannot be taken into consideration, their theoretical underpinnings are not solid. The analysis of the relation between uncertainty and investment in Sarkar (2000) is based on the cumulative probability of investment within a certain period after the creation of the investment opportunity; but when aggregate data are used (as in the previously mentioned empirical studies), the number of years that have passed since the investment opportunity has been created stays indeterminate. All that is measured, therefore, is the average effect of uncertainty on investment at each point in time, and not its cumulative impact once the investment opportunity has been created. Moreover, we show that the relation hinges on the length of the period chosen.

Clearly, the greatest difficulty with the empirical implementation is that, in general, it is not easy to collect data on investment delays. However, exploiting a firm-specific sample of inward investment into Central and Eastern European Countries (CEECs) by foreign transnational companies (TNCs), it is feasible to identify a unique starting date of the investment opportunity, i.e. the fall of the Berlin Wall. In fact, before 1989 foreign direct investment (FDI) in the CEECs from Western countries was virtually prohibited, with the only (partial) exception being Hungary. Starting from 1990, instead, the sudden removal of restrictions allowed FDI volumes to rise. Such a peculiar institutional context is also confirmed by the data, showing how FDI inflows in the CEECs passed from an average of US$ 59 million in the period 1985–89, to US$ 300 million in 1990 and US$ 2,448 million in 1991.[3]

Hence, in the context of the 'natural experiment' of transition, it becomes possible to measure the time spell occurred between the creation of the investment opportunity (in principle, end of 1989) and the investment undertaken by the first TNC entering in a given market. In particular, the collected sample allows us to directly test the link between uncertainty and investment through the hazard rate, i.e. the probability of investment given that the firm has not invested yet. In fact, as uncertainty is one of the parameters in the calculated hazard function, it can be directly estimated with maximum likelihood. In addition, the hazard approach not only enables a test of the effect of uncertainty on investment in Eastern Europe, but it also gives the opportunity to estimate the impact of other explanatory variables on the hazard rate of FDI, such as gravity-type variables (population, market size

[3]The main source of macroeconomic data on FDI is UNCTAD, *World Investment Report*, over various years.

and distance), labour cost, industry size, minimum efficient scale, speed of liberalization and the impact of trade agreements.

As a result, rather than testing the implications of a real-option model, the aim of this article was to test the real-option model itself, together with its relevant implications, by deriving an explicit function for the hazard rate of investment and structurally estimating it through microeconomic data on inward investment in Eastern Europe. For this purpose, the article is organized as follows. Section II derives the hazard rate of investment in a standard real-option model and briefly explains its properties. In section III, we set up the estimation models and discuss the data. Section IV examines the empirical results, with section V providing some refinements of the original model specifications. Implications and conclusions follow.

II. The hazard rate of investment

The theory of investment under uncertainty states that a firm should invest when the value of investment exceeds its cost by the (option) value of waiting to invest. Following Sarkar (2000), we normalize the cost of investment to 1 and assume that the earnings stream x follows a geometric Brownian motion,

$$\mathrm{d}x_t = \mu x_t \,\mathrm{d}t + \sigma x_t \,\mathrm{d}z_t \tag{1}$$

where μ is the (constant) drift rate, σ the (constant) standard deviation and $\mathrm{d}z$ the increment of a standard Wiener process. Denoting the correlation of the project with the market portfolio with ρ, the market price of risk with λ and a constant r as the risk-free rate, Sarkar (2000) shows that the project value (i.e. the net present value (NPV) of the project when accepted) can be written as $(x/\psi - 1)$ where $\psi = r + \lambda\rho\sigma - \mu$, while the value of the option to invest is the solution to an ordinary differential equation and can be written as $\Upsilon(x) = Ax^{\alpha}$, where

$$\alpha = \frac{1}{2} - \frac{\mu - \lambda\rho\sigma}{\sigma^2} + \sqrt{\left(\frac{1}{2} - \frac{\mu - \lambda\rho\sigma}{\sigma^2}\right)^2 + \frac{2r}{\sigma^2}} \quad \text{and} \quad A = (x^*)^{1-\alpha}/\psi\alpha.$$

The optimal investment rule, therefore, is to invest when $x \geq x^*$ (the value of earnings that triggers the investment decision), where $x^* = \alpha\psi/(\alpha - 1)$. As the option value increases with uncertainty, the critical value of investment increases when uncertainty gets higher. So, firms will normally require a higher profitability when uncertainty increases. Intuitively, people have hence assumed that a higher uncertainty also induces a longer period of waiting to invest. Sarkar (2000) points out instead that a higher uncertainty also changes the probability that the critical value x^* will be reached before a specific date, thus generating nonlinearities in the relationship between investment and uncertainty.

In particular, when current time is zero, the probability of reaching the trigger value x^* within some time period t can be written as

$$F(t, x_0) = \Phi\left(\frac{\ln[x_0(1 - 1/\alpha)/\psi] + \zeta t}{\sigma\sqrt{t}}\right) + \left(\frac{\psi}{x_0(1 - 1/\alpha)}\right)^{\gamma} \Phi\left(\frac{\ln[x_0(1 - 1/\alpha)/\psi] - \zeta t}{\sigma\sqrt{t}}\right) \tag{2}$$

where x_0 is the value of x at $t = 0$, $\Phi(\cdot)$ is the cumulative density of a standard normal distribution, $\zeta = (\mu - \frac{1}{2}\sigma^2)$ and $\gamma = (2\mu/\sigma^2) - 1$. By differentiating equation (2) with respect to t we derive the density function

$$f(t, x_0) = \varphi\left(\frac{\ln[x_0(1 - 1/\alpha)/\psi] + \zeta t}{\sigma\sqrt{t}}\right) \frac{\frac{1}{2}\{\zeta t - \ln[x_0(1 - 1/\alpha)/\psi]\}}{\sigma t\sqrt{t}} - \left(\frac{\psi}{x_0(1 - 1/\alpha)}\right)^{\gamma} \varphi\left(\frac{\ln[x_0(1 - 1/\alpha)/\psi] - \zeta t}{\sigma\sqrt{t}}\right) \frac{\frac{1}{2}\{\zeta t + \ln[x_0(1 - 1/\alpha)/\psi]\}}{\sigma t\sqrt{t}}. \tag{3}$$

Given the density and the cumulative density of investment at time t, the hazard rate of investment at time t, $h(t, x_0)$ is defined as[4]

$$h(t, x_0) = \frac{f(t, x_0)}{[1 - F(t, x_0)]}. \tag{4}$$

In our specific case, then, the hazard rate is calculated by plugging equations (2) and (3) into equation (4).

A numerical simulation of equation (2), reported in Figure 1, replicates the result of Sarkar (2000). However, it also shows that the shape of the relation between uncertainty and the cumulative probability of investment within τ years depends very much on the choice of τ. Although ancillary parameter values are as in Sarkar (2000), that is $\mu = 0$, $r = 0.1$, $\rho = 0.7$, $\lambda = 0.4$ and $x_0 = 0.1$, his result of a nonlinear relationship between uncertainty and the probability of investment holds only for intermediate values of τ, such as $\tau = 5$. For sufficiently low (high) levels of τ there is a positive (negative) relationship between uncertainty and the probability of investment.

For an empirical analysis, it is more useful to investigate the same relationship through the hazard rate, as the latter depends only on an observable variable (elapsed time since the creation of the investment opportunity), rather than on an arbitrary choice variable (τ).

Figure 2 plots the hazard rate of investment calculated in equation (4) for different values of uncertainty, where parameter values are as above. The

[4]See Kiefer (1988) or Greene (1999) for a general treatment of duration data and hazard functions.

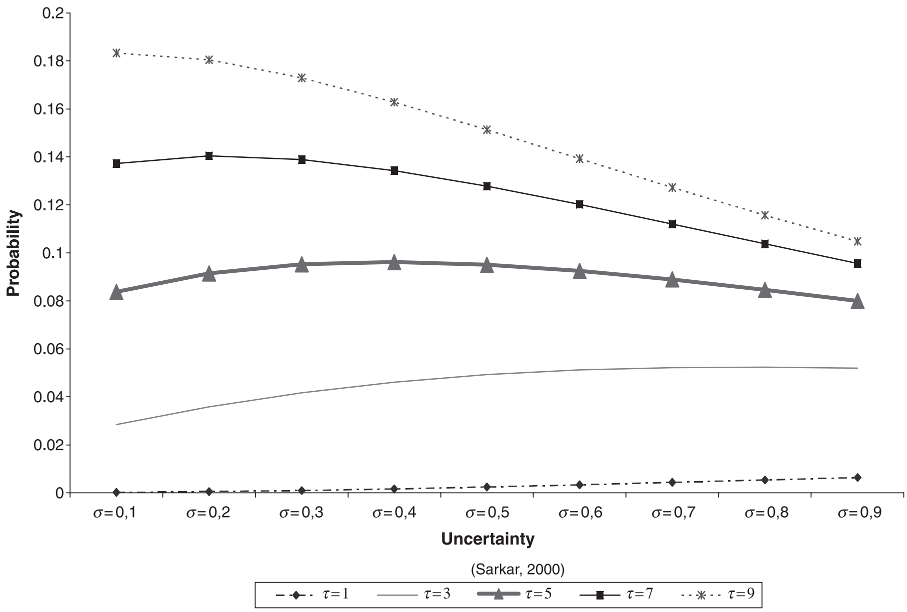

Figure 1. The probability of investment before τ. The probability of investment before τ is calculated according to equation (2), with $\mu = 0$, $r = 0.1$, $\rho = 0.7$, $\lambda = 0.4$ and $x_0 = 0.1$

hazard rate is actually humped for all levels of uncertainty. When the investment opportunity has just been created, the hazard increases in volatility. When the investment opportunity exists for a longer period, instead, the hazard decreases in volatility. The reason is that, if uncertainty is low, then the probability that a given investment trigger has not been reached over time is relatively high. On the contrary, a higher uncertainty in early periods increases the chances of quickly reaching the value of earnings that triggers the investment decision, despite the fact that the trigger is higher at higher uncertainty levels. The latter is the line of argument put forward by Sarkar (2000), here reproduced within a more general result.

Moreover, there is another source of nonlinearity in the investment–uncertainty relationship, as the shape of the hazard rate also depends on the initial value of the profitability variable x_0. When x_0 is increased from 0.1 to 0.14, for example, the hazard function decreases for all levels of uncertainty while increasing in volatility (see Figure 3). Decreasing x_0 to levels <0.1 preserves the humped shape of the hazard rate, but the peak shifts to the right for lower x_0s. Therefore, with a low uncertainty, we would observe relatively later investments in low-profit (low when the investment opportunity was created) industries, while postponed investments would also be observed in high-profit industries facing a relatively high uncertainty.

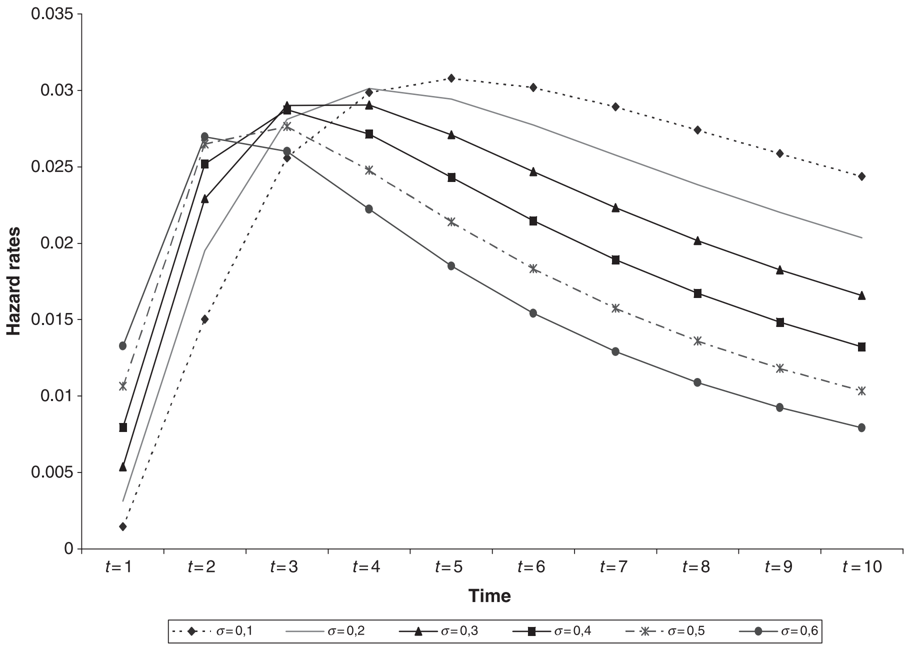

Figure 2. The hazard rate of investment based on a real-option model with $x_0 = 0.1$. The hazard rate is calculated as $h(t, x_0) = f(t, x_0)/[1 - F(t, x_0)]$ with $F(t, x_0)$ defined in equation (2) and $f(t, x_0)$ in equation (3)

III. Data description and econometric approach

The empirical literature has tested the effect of uncertainty on investment, expecting a negative relation between both variables. By explicitly calculating the hazard rate of investment we have instead shown that the relation between uncertainty and investment critically depends on the amount of time during which the firm has the option to invest at its disposal. So the relation between uncertainty and investment is far from clear when analysing aggregate investment data.

Moreover, in analysing the effect of uncertainty on investment, there have only been indirect attempts to estimate real-option models using reduced-form equations. In this article, we instead directly estimate a structural model of the hazard rate of investment from the basic real-option model of a lumpy investment (see Dixit and Pindyck, 1994). Given the arguments above, such a structural estimation seems to be a daunting task, but the sudden market liberalization in the CEECs in the late 1980s provides us with a clear starting date for creating a sample of investment opportunities. Given a set of 48

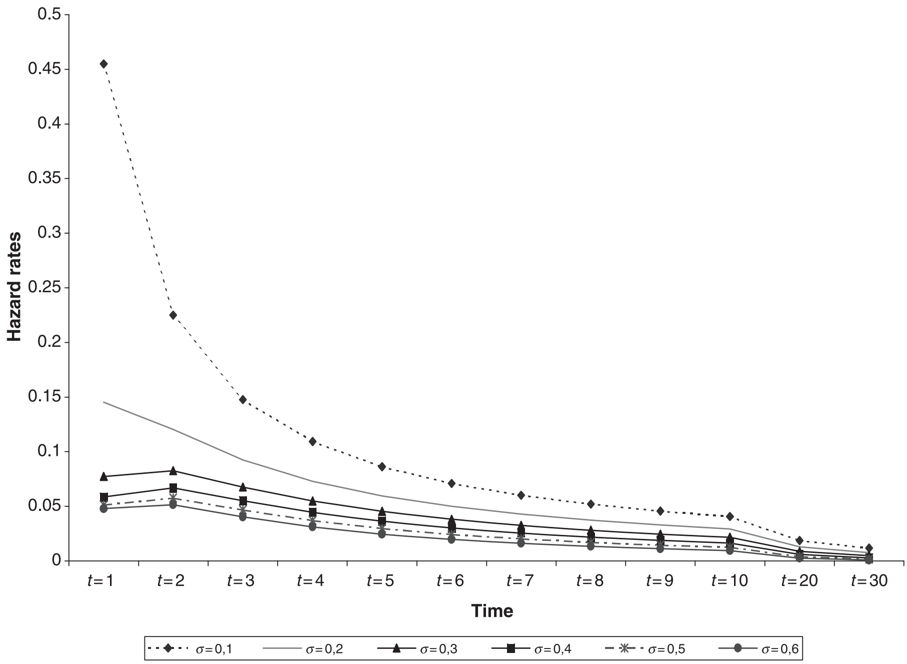

Figure 3. The hazard rate of investment based on a real-option model with $x_0 = 0.14$. The hazard rate is calculated as $h(t, x_0) = f(t, x_0)/[1 - F(t, x_0)]$ with $F(t, x_0)$ defined in equation (2) and $f(t, x_0)$ in equation (3)

industries in seven CEECs included in the PECODB database,[5] we generate a sample of 336 investment opportunities for TNCs within the period 1990–98. For each country/industry pair, it is possible to measure the investment spell, i.e. the time elapsed from the start of the liberalization process to the moment in which the first investment has been undertaken. Endowed with this information, we are then able to estimate the hazard function of the first investment by a TNC in a particular industry within one of these countries.

More specifically, our structural model of the hazard rate will be contrasted with a reduced-form (Cox-proportional) model of the hazard. Estimates comparing these two approaches with the same explanatory variables are presented in the subsequent sections.

So as to set up the estimation models, let x_{ij0}, the profitability of investment in country i in industry j at time $t = 0$, be a monotonic function of exogenous

[5]The PECODB database is a firm-specific collection of 4,200 FDI operations in the CEECs in the period 1990–98. The database excludes small marketing ventures, including only actual production units controlled by TNCs. In terms of validation, the database is able to account for almost 70% of the region's total FDI inward stock as registered by official statistics. The countries included in the present analysis are Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovak Republic and Slovenia. A list of the considered industries is reported in the Appendix.

variables y_{ij0}, i.e. $x_{ij0} = 2\ \exp(y'_{ij0}\theta)/[1 + \exp(y'_{ij0}\theta)]$, where θ is a vector of parameters to be estimated.[6] The vector y_{ij0} includes variables extensively employed in the empirical literature on foreign investments such as gross domestic product (GDP) per capita (gdppc), population (pop), distance (dist), all taken in logs, and the comparative advantage of the host country in terms of labour costs (relwage).[7]

As the models are tested at the industry level, while the theory is based on a single-project partial equilibrium model, we have to address the issues of functional form mis-specification and heterogeneity. The latter may arise because investments in different industries may have different distributions, because of differences in the minimum efficient scale, industry sizes or sunk costs. To control for this aggregation problem (see Kiefer, 1988), we include among the exogenous variables the (log) average size (indsize) of each industry in each country, and the (log) minimum efficient scale (MESdom) of domestic firms in each industry (see Appendix for a detailed description of the data).

Another possible bias derives from the fact that the dependent variable in our estimates (the investment spell) critically depends on the choice of the initial year in which the investment opportunity was created. Although, in principle, the natural experiment of transition points to 1989 as the initial year from which one should start measuring the investment spell, there is evidence that in Eastern Europe different countries opened up to FDI establishing different modalities of privatization/liberalization in different years. Therefore, so as to control this further source of heterogeneity, we interact the variable indsize with a variable measuring the pattern of liberalization in each country in a given year (lib). The latter variable, previously employed by Holland and Pain (1998) and Carstensen and Toubal (2004),[8] is an index with a scale from 1 to 5 representing the method of privatization, where 1 is the most impeding method for TNCs (vouchers) and 5 is the most favourable (sales to outside owners only). As a result, the interaction variable is a country, industry and time-dependent variable measuring the size of each industry corrected for the legal entry barriers.

Finally, given our theoretical set-up, we also have to control for the different impact of industry structure on the investment decisions. We have introduced a set of dummies partitioning industries into high, medium and low sunk costs, based upon the Davies and Lyons (1996) classification reported in

[6]So as to be consistent with the normalization of costs to 1, we bounded the profitability of investment x_{ij0} to the [0, 2] interval. The main results are, however, not affected by different values of the upper bound, as long as the relation between x_{ij0} and y_{ij0} is monotonic.

[7]For this purpose, the 1998 *World Investment Report* from UNCTAD provides a good survey of the main FDI trends and determinants.

[8]We are grateful to Farid Toubal for making the variable available to us.

Appendix. In particular, industries are classified as having *high* sunk costs when, based on their statistical classification of economic activities in the EU (NACE) code, the industry is both advertizing and R&D intensive. They are considered as having *medium* sunk costs when the industry is either R&D or advertizing intensive, and as having low sunk costs otherwise.

Under the parameter restrictions, $r = 0.1$, $\rho = 0.7$ and $\lambda = 0.4$, we subsequently derive the likelihood as a function of parameters μ, θ and σ. Parameters are then estimated by maximum likelihood estimation.[9] More specifically, we know that after the (conventional) start of transition in 1989, the first investments have taken place in our sample in 1990, which hence represents $t = 1$. Industries in countries where no investment has taken place before 1999 are (right) censored observations. Let $T = 9$ denote the last year (1998) for which data are available in the PECODB database. As our data are not continuous, a discrete version of the continuous density function is taken. Following Kiefer (1988), the integrated hazard of investment in sector j in country i can then be written as

$$H_{ij}(t\,|\,\theta,\sigma,\mu) = \sum_{s=1}^{t} h_{ij}(s\,|\,\theta,\sigma,\mu) \tag{5}$$

where $h_{ij}(s|\theta, \sigma, \mu)$ are the hazard rates as in equation (4), calculated under the previously imposed restrictions on r, ρ and λ, and given the distribution of x_{ij0} and the parameters μ, θ and σ to be estimated. The associated log-likelihood function to estimate is thus

$$\ln L(\theta,\sigma,\mu) = \sum_{i}\sum_{j} d_{ij}\ \ln[h_{ij}(t\,|\,\theta,\sigma,\mu)] - H_{ij}(T\,|\,\theta,\sigma,\mu) \tag{6}$$

where $d_{ij} = 1$ for uncensored observations and $d_{ij} = 0$ if instead the observation is censored. Inference about the parameter values can be done in the usual way.

The estimation of our real-option model on actual data implies a trade-off. From one side, to properly account for the nonlinearities in the hazard rate of investment derived from the real-option model, it is crucial to analyse a sample of investments on which we can measure the time spell since the actual creation of the investment opportunity. As we have seen, the latter can be done exploiting the 'natural experiment' of transition, i.e. working with a sample of TNCs that have invested in the CEECs, where FDI were virtually prohibited before 1989.

From the other side, however, real-option models *à la* Sarkar (2002) can be solved in their structural form only by imposing a time-invariant volatility. The

[9]Parameters r, ρ and λ can be considered as scaling constants; a change in their value does not significantly affect the estimated hazard rate of investment.

assumption might seem at odds with the empirical evidence of transition, as intuition suggests that uncertainty decreases over time during the transition period. However, the empirical evidence from volatility in emerging markets that opened up to foreign investments shows that uncertainty is actually fairly constant over time. To the best of our knowledge, only Bekaert and Harvey (1997) find a downward trend in stock market volatility when emerging markets open up to foreign investors. Later studies (De Santis and Imrohoroglu, 2000; Han Kim and Singal, 2000) argue, however, that their result is based on a sample of countries out of which only three showed a significant decrease in volatility, while one an increase. Using a much richer sample of countries, the later papers do not find a significant overall effect of liberalization on volatility up to 5 years after the liberalization date.

Although the evidence suggests a constant uncertainty over time within a country after liberalization, uncertainty is likely to differ across countries and industries. Hence, in our model, we will estimate a country- and industry-specific parameter for uncertainty, σ_{ij}. In particular, we assume σ_{ij} to be composed of a constant (e.g. the 'implied volatility' of the option value, σ_{const}) and a function of a time-invariant exogenous variable (indunc_{ij}), which is a proxy for the uncertainty surrounding the profitability of investment in each country–industry pair.[10] Hence

$$\sigma_{ij} = \sigma_{\text{const}} + \beta \times \text{indunc}_{ij} \tag{7}$$

where β and σ_{const} are parameters to be estimated. The exogenous variable indunc_{ij} is the average coefficient of variation of the earnings before interest and taxes (EBIT) of a sample of firms (both domestic and multinationals) currently operating in the seven countries/48 industries considered.[11] The data source for the uncertainty variable is the AMADEUS data set, provided

[10]Given the theoretical properties of the real-option-based hazard rate, trying to proxy σ through the traditional country-specific measures of uncertainty employed in the literature would yield (and has indeed yielded in our estimates) an identification problem. This is because of the collinearities arising in the maximization of the likelihood function among variables related to profits and variables related to uncertainty, once these are all measured along the *i*th (country) dimension of the data. The intuition comes from a comparison of Figures 2 and 3: a variation along the profitability dimension has *ceteris paribus* a nonlinear effect on the uncertainty or, better, different combinations of initial profit conditions and uncertainty can yield the same hazard rate. Hence, a likelihood function where these two variables are measured along the same (country) dimension is likely to present points of local optima or saddle points.

[11]So as to proxy uncertainty through firms' income statements, we have to retrieve a measure which is bounded between 0 and infinity and at the same time does not suffer from a bias induced by firm's size. As a result, for each firm we have calculated the ratio between the yearly EBIT and its average over the period (thus normalizing for firm's size). Subsequently, we have taken the standard deviation over time of these ratios. Finally, for each of the 336 country/industry pairs, we have taken the average of these firm-specific coefficients, thus retrieving a dimensionless coefficient of variation ranging in our dataset from a minimum of 0.28 to a maximum of 8.42. For example, in the clothing industry in Hungary (NACE 18), the EBIT of our available sample of 176 firms yielded a coefficient of variation of 2.74 over the considered period.

by the Bureau Van Dijck, a consulting firm operating in Brussels, and containing balance sheet data of a sample of roughly 5,000,000 companies operating in Europe. Of the almost 180,000 companies recorded in the seven countries considered, we have restricted our analysis to the 32,083 firms for which data are available for at least four consecutive years, so as to have a meaningful estimate of each firm's EBIT standard deviation. Hence, on an average, the EBIT coefficient of variation is calculated with 95 firms per observation.[12]

The method of a structural estimation of the hazard rate in a real-option framework, via the maximization of the associated likelihood function in equation (6), will be compared with more traditional reduced-form estimations of the hazard, which do not directly test the investment–uncertainty relationship but rather impose an arbitrary function on the 'baseline' hazard, or leave the same baseline unspecified.

In particular, in the option-related literature, Hurn and Wright (1994) and Favero *et al.* (1994) use a hazard model approach using data on the time between the development of an oil field and its discovery. They write the hazard as the product of the baseline hazard (both non-parametric and parameterized as a Weibull function) and the covariates (including uncertainty), so they examine the effect of uncertainty on the waiting period. Among the few empirical studies that have looked at the entry timing of FDI using a hazard function approach, Tan and Vertinsky (1996) analyse the timing of FDI by Japanese electronics firms in the USA and Canada. Using a non-parametric hazard model they find, among other results, that strong market growth in the host country leads to a more rapid undertaking of inward FDI. A related study is given by Kogut and Chang (1996), who consider the spell between sequential investments by Japanese firms in the USA. They show that initial investments serve as platforms for subsequent investments. More recently, Garcia Blandon (2001) studied the timing of FDI in the banking sector in Spain using a hazard approach.

As a benchmark to be used in the comparison with our structural estimation, we have opted for the Cox-proportional model, where the uncertainty variable indunc_{ij} enters the hazard rate together with other exogenous variables affecting the hazard, as

[12]To the best of our knowledge, the quoted studies cited in Section I do not report the correlation between uncertainty in the macro variables employed as proxies and uncertainty in entrants' profits. Hence, to rule out a systematic difference between the average uncertainty employed in the estimates, measured at the industry level, and the uncertainty actually faced by the first movers TNCs, we have checked the correlation between our measure of industry-specific uncertainty and the coefficient of variation of the EBIT of the investing TNCs, with respect to which the investment spell has been measured. The figure we obtained revealed a positive and significant correlation of 0.23 (calculated on 111 available observations, with a P-value of 0.016 for the two-tailed test).

$$\lambda_{ij}(t) = \tilde{\lambda}(t)e^{y'_{ij0}\beta_0 + \text{indunc}_{ij}\beta_1} \tag{8}$$

where y_{ij0} is a vector of exogenous variables as defined before, $\tilde{\lambda}(t)$ the baseline hazard, and β_0 and β_1 are the parameters to be estimated. The Cox-proportional model leaves the baseline hazard unspecified, providing estimates of the coefficients β_0 and β_1, but no direct estimate of $\tilde{\lambda}(t)$, hence maximizing a partial log-likelihood function corrected for censoring. As $\partial \ln \lambda(t)/\partial y_{ij0} = \beta_0$ and $\partial \ln \lambda(t)/\partial\, \text{indunc}_{ij} = \beta_1$, the estimated coefficients (see Table 1) can be interpreted as the constant proportional effect of y and the uncertainty indunc on the conditional probability of investing within a certain period.[13]

Our structural model for the hazard[14] is instead more efficient, as it takes into account the nonlinearities in the uncertainty–investment relation. However, the latter model, if not correctly specified, can lead to inconsistent estimates in case of mis-specification. To tackle this problem, we have performed a specification analysis for all our estimated models, by examining the generalized residuals, ε, which equal the integrated hazard $H_{ij}(t|\theta, \sigma, \mu)$ of equation (5). If the model is correctly specified, the generalized residuals are exponentially distributed. Therefore, in the absence of censoring, the population moments expectations, $E[\varepsilon^p]$, equal p! The conditional moment approach to specification testing exploits the fact that if the model is correctly specified the sample average moments (evaluated at the estimated parameters and the observed explanatory variables) should be close to the population moments expectations. For censored observations, the centred moment conditions are $r_p = 0$. Let $\hat{r}$ be the vector with the observed centralized moments, then the elements of the vector are

$$\hat{r}_p = \frac{1}{NM}\sum_i \sum_j m_{ij}^p$$

with N and M being the number of countries and industries, respectively, and

$$m_{ij}^p = \left(\varepsilon_{ij}^p - p! + (1 - d_{ij})\sum_{k=0}^{p-1}\frac{p!}{k!}\varepsilon_{ij}^k\right) \quad \text{with } p \geq 2.$$

Pagan and Vella (1989) show that under some regularity conditions $\sqrt{NM}\hat{r}$ is asymptotically normal with mean 0 and covariance matrix Σ. Hence, a Wald specification test-statistic for $\hat{r} = 0$ is given by $NM\hat{r}'\Sigma^{-1}\hat{r}$, which is

[13]As noted by Kiefer (1988), this is the analog, in a hazard function setting, of the usual partial-derivative interpretation of a linear regression coefficient.

[14]See equation (4) for our specification of the parametric model of the hazard rate, and Tables 2 and 3 for the estimation results of the same model.

χ^2-distributed with the dimension of the vector of moments as the degree of freedom.[15] The test-statistic is then reported at the bottom of Tables 1–3 presenting our results.

IV. Results

The estimation of several specifications of the hazard function through a Cox-proportional hazard model yields (see Table 1) the traditional result reported by the estimations of the investment–uncertainty link: uncertainty is significantly and negatively related to the investment probability through the effect it generates on the mean profit. Market variables (population and per capita GDP) as well as the comparative advantage of the country in terms of labour costs

TABLE 1

Estimation of the Cox proportional hazard

	(1)	*(2)*	*(3)*	*(4)*
pop	1.74** (6.64)	1.73** (6.61)	1.73** (6.62)	1.71** (6.31)
gdppc	3.06** (4.71)	3.02** (4.67)	3.03** (4.68)	2.96** (4.44)
relwage	0.42** (3.50)	0.42** (3.52)	0.43** (3.53)	0.43** (3.54)
dist	−1.34** (−4.61)	−1.35** (−4.66)	−1.36** (−4.67)	−1.37** (−4.65)
indsize	0.18** (2.60)	0.17** (2.52)	0.18** (2.53)	0.21* (1.94)
indsize*lib	—	—	—	−0.02 (−0.41)
indunc	−0.13* (−1.86)	−0.14* (−1.93)	−0.14* (−1.95)	−0.14** (−1.96)
MESdom	—	—	0.02 (0.28)	0.02 (0.26)
med	−0.16 (−1.10)	—	—	—
high	−0.17 (−0.94)	−0.09 (−0.52)	−0.10 (−0.56)	−0.10 (−0.58)
Log-likelihood†	−1,263.39	−1,263.99	−1,263.96	−1,263.87
NM	336	336	336	336
Specification test				
Central moment II	−0.11 (−0.77)	−0.11 (−0.78)	−0.11 (−0.80)	−0.11 (−0.80)
Central moment III	−0.42 (−0.73)	−0.42 (−0.74)	−0.44 (−0.77)	−0.44 (−0.79)
Central moment IV	−1.73 (−0.62)	−1.74 (−0.63)	−1.81 (−0.66)	−1.81 (−0.68)
Central moment V	−8.72 (−0.58)	−8.97 (−0.58)	−9.10 (−0.61)	−9.10 (−0.65)
H_0: joint moments, mean = 0, $\chi^2(4)$	8.23	8.35	8.41	8.51
H_0: zero-slope coefficients, χ^2(no. of var)	30.16**	30.10**	31.27**	31.73**

Notes:
t-statistics in parentheses; estimations based on hazard function reported in equation (8).
Significant at the **5% level or more and at the *10% level.
†The Cox-proportional specification estimates a partial log-likelihood function.

[15] In particular, as noted by Greene (1999), $\Sigma = [B'B - B'D(D'D)^{-1}D'B]/NM$, where B is the matrix whose ith row is the vector of central moments and D is the matrix of the scores of the likelihood function.

positively and significantly affect the probability of undertaking an investment. The average size of the industry also significantly increases the probability of an earlier investment, while the distance to the host country significantly decreases it. The results take into account differences in industry, being robust against different specifications of the sunk costs (Column 1 vs. 2–4). Minimum efficient scale, measured by the (log of) median firm's employment of domestic firms in each industry calculated on the set of considered countries,[16] is not significant (Column 3) and its inclusion does not change the results. Finally, the results are robust to the inclusion of the interaction term between the average industry size and the variable measuring the pattern of liberalization in each country in a given year.

All the estimated models passed the specification test on the higher order central moments m_{ij}^{p} of the generalized residuals, as confirmed by the joint chi-squared test-statistic reported in Table 1. However, a further specification test available for Cox proportional models evaluates the non-zero slope in a generalized linear regression of the scaled residuals on functions of time (Grambsch and Therneau, 1994), and hence explicitly takes into account eventual nonlinearities arising in the estimation of the hazard function. The test of zero slope is in fact equivalent to testing if the baseline hazard $\tilde{\lambda}(t)$ is constant over time. The test-statistic is chi-squared-distributed, and the null hypothesis is strongly rejected, for all the Cox-proportional model specifications, at the 95% level of significance. This result indirectly confirms the theoretical implication of nonlinearities in the relation between investment and uncertainty (see Figure 2), which thus leads to a mis-specification of standard models of the hazard.

For a better understanding of the investment–uncertainty relationship, it is, therefore, worth moving from a reduced-form specification to the structural estimation of our theoretical real-option-based hazard rate of investment, through the maximization of the associated likelihood function in equation (6).

Table 2 reports the results of this exercise on the basis of covariates measured at initial conditions x_{ij0}. As it can be seen, for all the model specifications, the covariates related to profitability are correctly signed and significant, with minor changes from one specification to the other. This is an indication that, controlling for sunk costs, industry size, minimum efficient scale and heterogeneity in the start of the liberalization process across countries (Columns 1–5), the theoretical model is able to properly fit the data explicitly taking into account the nonlinearities previously mentioned. The drift rate μ at the basis of the stochastic evolution of profits over time (see equation 1) is estimated within the econometric model and takes the value

[16]As in Geroski (1991), we use median employment at the firm level to calculate minimum efficient scale. We use domestic and not TNCs' employment to avoid introducing endogeneity in the estimates, although the two measures turned out to be highly correlated.

TABLE 2

Estimation of the real-option hazard model with initial covariates

	(1)	(2)	(3)	(4)	(5)
const	−19.34** (−2.07)	−17.96** (−2.18)	−16.57** (−2.00)	−14.79* (−1.79)	−18.34* (−1.71)
pop	2.74** (2.87)	2.60** (3.03)	2.49** (2.88)	2.31** (2.65)	2.68** (2.71)
gdppc	4.97** (2.54)	4.69** (2.69)	4.45** (2.54)	4.06** (2.31)	4.83** (2.37)
relwage	0.24 (1.45)	0.22* (1.94)	0.18 (1.30)	0.17 (1.25)	0.22 (1.38)
dist	−1.20** (−4.69)	−1.18** (−4.71)	−1.16** (−4.57)	−1.13** (−4.41)	−1.17** (−4.59)
indsize	0.24* (1.72)	0.21* (1.94)	0.17 (1.56)	0.25 (1.59)	0.35* (1.73)
indsize*lib	—	—	—	−0.06 (−0.80)	−0.08 (−0.88)
MESdom	—	—	−0.08 (−0.92)	−0.07 (−0.88)	−0.14 (−1.21)
med	0.08 (0.37)	—	—	—	0.26 (0.96)
high	0.36 (1.24)	0.31 (1.22)	0.31 (1.27)	0.31 (1.28)	0.48 (1.55)
σ_{const}	−2.10** (−10.71)	−2.09** (−11.02)	−2.07** (−11.29)	−2.08** (−10.62)	−2.09** (−10.63)
indunc	0.04 (0.48)	0.03 (0.45)	0.02 (0.28)	0.02 (0.28)	0.03 (0.37)
$\tilde{\mu}$	−3.01** (−80.90)	−3.01** (−79.58)	−3.01** (−74.09)	−3.02** (−67.80)	−3.00** (−80.16)
Log-likelihood	−590.10	−590.18	−589.76	−589.45	−588.88
NM	336	336	336	336	336
Specification test					
Central moment II	0.07 (1.48)	0.07 (1.51)	0.08 (1.52)	0.09 (1.56)*	0.08 (1.54)
Central moment III	0.17 (0.67)	0.17 (0.67)	0.23 (0.78)	0.25 (0.80)	0.25 (0.79)
Central moment IV	0.76 (0.61)	0.85 (0.63)	1.17 (0.71)	1.29 (0.72)	1.26 (0.72)
Central moment V	4.64 (0.64)	5.11 (0.65)	6.91 (0.70)	7.65 (0.71)	7.35 (0.69)
H_0: joint moments, mean = 0, $\chi^2(4)$	9.22	9.53*	10.43*	10.55*	10.12*

Notes:
t-statistics in parentheses; estimations based on likelihood function reported in equation (6).
Significant at the **5% level or more and at the *10% level.

$\mu = 0.047$ with a very low standard deviation, i.e. an implied average growth rate, in the countries considered, of 4.7% per year, which does not seem unreasonable for transition countries.[17]

Contrary to the previous studies, where the effects of uncertainty were measured on the mean value of profits (i.e. among the profit-related regressors), structurally estimating the 'true' real-option specification allows us to directly relate the standard deviation σ_{ij} of the stochastic evolution of profits to our measure of country- and industry-specific uncertainty (indunc), as from equation (7). We find this proxy to be correctly signed in our model specifications but not significant. Rather, the data show support for the assumption, typical of real-option models, of a constant 'implied volatility' in the stochastic evolution of profits (positive and significant σ_{const}), with a value in our sample of countries/industries of around 10%.[18] Most importantly, our estimations of the real-option-based hazard show that the central moments (II–V) of the generalized residuals are, but one, all within one standard deviation from zero, and hence the model is correctly specified.[19]

Insofar, the result suggests that the negative effect of uncertainty on investment works through its effect on profitability rather than on the value of waiting to invest and that nonlinearities are likely to be present in the relationship. The result, therefore, supports the view of Ghosal and Loungani (2000) that the investment–uncertainty relationship may depend on other channels than option one. There is a value of waiting, although, but it is not related to our measure of uncertainty.

V. A refinement: time-varying covariates

The hazard rate calculated insofar has allowed us to measure the effects of uncertainty on investment taking into account initial conditions x_{ij0}. However, it is interesting to check whether our results also hold when profit-related covariates are time dependent. Through this refinement, it is possible to take into account eventual pro-cyclical effects of FDI and, in our specific case, to better measure the ongoing transition of the considered countries towards a market economy. Let x_{ijt}, the profitability of investment in country i in industry j in year t, be a monotonic function of exogenous variables y_{ijt} as in the previous case, where y_{ijt} includes as before our profit-related variables,

[17]For technical reasons linked to the convergence algorithm, the estimated parameter reported in Tables 1–3 is $\tilde{\mu}$, defined as $\tilde{\mu} = \ln[\mu/(1-\mu)]$, where $0 < \mu < 1$. Hence, once $\tilde{\mu}$ is estimated, the actual μ can be otained by the inverse transformation $\mu = \exp(\tilde{\mu})/[1+\exp(\tilde{\mu})]$.

[18]As in the case of μ, for technical reasons linked to the convergence algorithm, the actual value of σ_{ij} can be derived by the transformation $\sigma_{ij} = \exp(\tilde{\sigma}_{ij})/[1+\exp(\tilde{\sigma}_{ij})]$, where $\tilde{\sigma}_{ij}$ is estimated as from equation (7).

[19]However, the chi-squared test-statistic weakly rejects the joint moments mean to be equal to zero for some model specifications. We address the issue in section V.

now allowing them to vary over time. Again, under the same parameter restrictions for r, ρ and λ as in section IV, parameters μ, θ, σ_{const} and β can be estimated by maximum likelihood estimation. The discrete version of the integrated hazard with time-varying covariates of investment in sector j in country i can then be written as

$$\Lambda_{ij}(t \mid \theta, \sigma, \mu) = \sum_{s=1}^{t} \lambda_{ij}(s \mid \theta, \sigma, \mu) \tag{9}$$

where

$$\lambda_{ij}(s \mid \theta, \sigma, \mu) = \frac{f(s, x_{ijs})}{\left[1 - \sum_{t=1}^{s-1} f(t, x_{ijt})\right]}$$

is the (discrete) hazard given the density function calculated in equation (3) and for $s > 1$, while $\lambda_{ij}(1 \mid \theta, \sigma, \mu) = f(1, x_{ij1})$. The associated log-likelihood function is

$$\ln L(\theta, \sigma, \mu) = \sum_{i} \sum_{j} d_{ij} \ \ln[\lambda_{ij}(s \mid \theta, \sigma, \mu)] - \Lambda_{ij}(T \mid \theta, \sigma, \mu) \tag{10}$$

where $d_{ij} = 1$ for uncensored observations and $d_{ij} = 0$ if instead the observation is censored.

Table 3 shows how the results of this model specification are remarkably similar to the one without time-varying covariates, for both the profit-related variables and the estimates of the parameters μ and σ, always controlling for sunk costs, industry size, minimum efficient scale and heterogeneity in the start of the liberalization process across countries (Columns 1–3). The specification test does not initially support the hypothesis of a joint zero mean for the moments reported in Table 3, but, apart from the second, the higher order centred moments relative to their standard deviation display a rapid convergence towards zero, as confirmed by the associated t-statistic.

In the search for a better model specification, we use the time dimension of the covariates, which allows us to include in the estimation (Columns 4–6) also a dynamic effect linked to the trade liberalization across the CEECs and the European Union (EU). In particular, the EU-FTA and CEEC-FTA dummies take value 1 if, in the considered year, a bilateral free-trade agreement (FTA) has been signed by the CEECs, respectively, with the EU or with other CEECs, as reported in the Appendix. The alternative model design aims at taking into account the different strategies (vertical vs. horizontal FDI) that have been undertaken by the TNCs investing in the area, a relevant issue for the purpose of this article, as the two types of FDI might behave differently with respect to the investment–uncertainty relationship.

TABLE 3

Estimation of the real-option hazard model with time-varying covariates

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
const	−2.90 (−1.33)	−2.01 (−1.01)	−2.01 (−1.02)	−1.99 (−1.01)	−1.17 (−0.59)	−0.91 (−0.44)
pop	1.16** (4.16)	1.09** (4.03)	1.09** (4.33)	1.09** (4.32)	1.13** (5.26)	1.14** (5.07)
gdppc	1.58** (3.94)	1.51** (4.02)	1.52 (4.05)	1.51** (4.04)	1.32** (3.89)	1.26** (3.36)
relwage	0.47** (2.67)	0.44** (2.73)	0.44** (2.74)	0.44** (2.74)	0.37** (2.42)	0.25 (1.24)
dist	−1.03** (−5.44)	−1.00** (−5.47)	−1.00** (−5.48)	−1.00** (−5.50)	−1.11** (−6.60)	−1.14** (−6.48)
indsize	0.17 (1.53)	0.15 (1.47)	0.15 (1.52)	0.15 (1.54)	0.18* (1.65)	0.19* (1.71)
indsize*lib	−0.04 (−1.18)	−0.04 (−1.24)	−0.04 (−1.23)	−0.04 (−1.26)	−0.05 (−1.24)	−0.05 (−1.25)
MESdom	—	−0.12* (−1.89)	−0.12** (−2.08)	−0.12** (−2.07)	−0.13** (−2.02)	−0.13** (−1.96)
med	−0.11 (−0.81)	0.01 (0.05)	—	—	—	—
high	0.27 (1.24)	0.31 (1.51)	0.31 (1.61)	0.30* (1.66)	0.37* (1.79)	0.42** (2.02)
EU-FTA	—	—	—	0.48** (2.41)	—	0.27 (1.24)
CEEC-FTA	—	—	—	—	0.77** (2.17)	0.56 (1.54)
σ_{const}	−2.46** (−8.31)	−2.29** (−6.86)	−2.29** (−6.95)	−2.41** (−9.20)	−2.25** (−8.35)	−2.3** (−8.82)
indunc	−0.02 (−0.14)	−0.10 (−0.75)	−0.10 (−0.76)	−0.06 (−0.57)	−0.14 (−1.32)	−0.12 (−1.13)
$\tilde{\mu}$	−2.99** (−105.2)	−3.00** (−103.6)	−3.00** (−104.2)	−2.98** (−144.2)	−2.98** (−149.8)	−2.98** (−151.4)
Log-likelihood	−587.85	−586.01	−586.01	−581.12	−580.25	−579.38
NM	336	336	336	336	336	336
Central moment II	0.47 (1.69)*	0.64 (1.67)*	0.62 (1.69)*	0.18 (0.77)	0.35 (1.21)	0.17 (0.73)
Central moment III	1.19 (1.14)	2.79 (1.13)	2.75 (1.17)	0.30 (0.45)	0.83 (0.81)	0.17 (0.35)
Central moment IV	4.01 (0.91)	17.60 (0.88)	16.97 (0.89)	0.79 (0.35)	2.80 (0.65)	0.01 (0.00)
Central moment V	17.57 (0.77)	30.03 (0.79)	30.29 (0.79)	3.47 (0.31)	11.77 (0.57)	−1.23 (−0.09)
H_0: joint moments, mean = 0; $\chi^2(4)$	16.34**	16.51**	16.56**	8.77	11.11*	7.12

Notes:
t-statistics in parentheses; estimations based on likelihood function reported in equation (10).
Significant at the **5% level or more and at the *10% level.

As horizontal FDI tend to be market driven, they should respond positively to a liberalization among the CEECs (the CEEC-FTA dummy), because this increases the market access for the local TNCs' affiliates. Although vertical FDI might be captured in the previous model specification by the significance of the relative wages, a better control for this kind of TNCs' strategies is the explicit inclusion of a variable measuring the removal of trade barriers between the home and the host economy (the EU-FTA dummy), a factor to which vertical FDI are particularly sensitive. It is not surprising that both dummy variables are significant (Columns 4 and 5). More importantly, the general relationship between investment and uncertainty is robust to this richer model design, which tends to display consistent and significant signs for all the control variables (Column 6) and also passes more easily the specification tests.

Hence, we have an indication that the methodology of directly estimating the hazard rate of a real-option model is robust to different model designs, and can yield interesting results in the analysis of the investment–uncertainty relationship under different theoretical set-ups.

VI. Implications

The model also gives additional insights into our understanding of the patterns of FDI in Eastern Europe. According to Sinn and Weichenrieder (1997) FDI has been disappointingly low in Eastern Europe. We show that irreversible investment in the form of FDI can still be expected because of trade liberalization especially in industries that after the fall of the Berlin wall were characterized by low expected profitability and low uncertainty (e.g. regulated industries such as utilities) and in industries with high expected profitability and high uncertainty.

So as to provide some evidence of this finding, and as an example of the prediction power of our model, we have calculated the average hazard rates of foreign investment for specific industries j and countries i on the basis of our estimated coefficients of initial profitability x_{ij0}, drift rate μ and variance σ_{ij} reported in Table 2, with the same parameter values for r, ρ and λ employed throughout the article. For this purpose, Figure 4 (top) shows how a low expected profitability/low uncertainty industry (electricity and gas), and a high expected profitability/high uncertainty industry (finance) both display on an average a predicted hazard rate higher than a 'standard' industry such as electronics.

Furthermore, at the country level, while the high hazard rate of Poland is not unexpected, there is, for example, an evident discrepancy in the ability of attracting future FDI between Bulgaria and Romania (Figure 4, bottom), both of which did not join the European Union in its first wave of Eastern

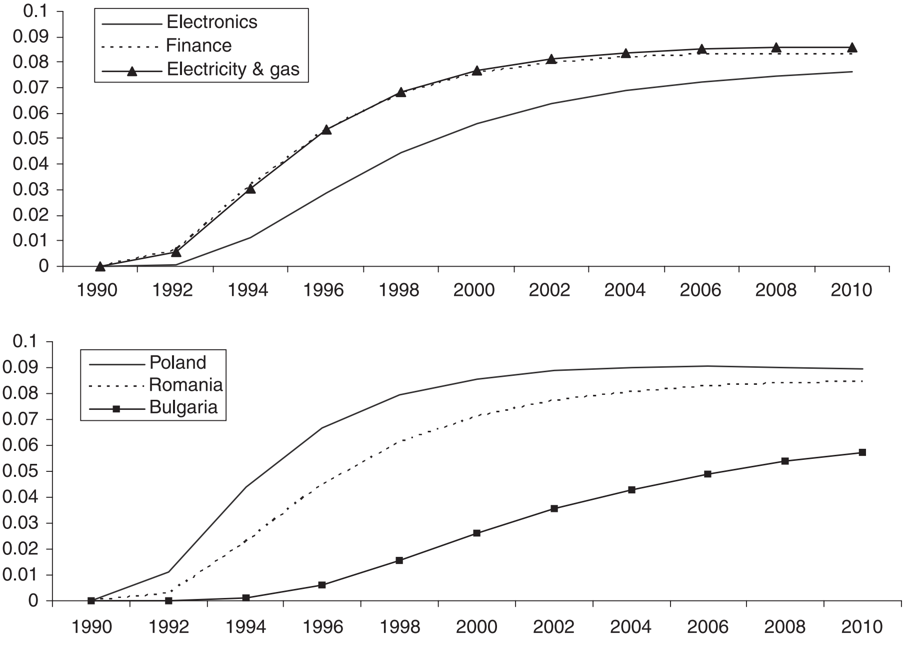

Figure 4. The predicted avarage hazard rates of investment in specific industries and countries. The reported hazard rates are the average over selected industries and countries of the *ij* hazards calculated on the basis of the estimated initial profitability x_{ij0} and variance σ_{ij}. In particular, $x_{ij0} = 2\ \exp(y_{ij0}\theta)/[1 + \exp(y_{ij0}\theta)]$, where y_{ij0} includes the parameter estimates and covariates given in Column 1 of the real-option model in Table 1. Similarly, σ_{ij} is calculated from equation (7) given the parameter estimates for σ_{const} and indunc in the same column. The parameter values for r, ρ and λ are the same as used throughout the paper.

enlargement. If adequate policy measures for encouraging FDI are be implemented by the Bulgarian government, there is the risk of a progressive widening in the integration path of this country with respect to the Romanian counterpart and, ultimately, to the same EU.

VII. Conclusion

This article sheds new light on the investment–uncertainty relationship within the literature on irreversible investments, directly estimating the implied hazard function of a real-option model. We find a direct support for the hypothesis of a nonlinear relation between investment and uncertainty, with the nonlinearities being of an even more complex nature than the theory had originally predicted. As such, any empirical study not taking all these interactions into account leads to an approximate, indirect assessment of the investment–uncertainty relationship. Within this respect, the study provides some evidence that the negative impact of uncertainty on investment reported in the literature has to be attributed to its effect on expected profits, rather than to the value of waiting option. More specifically, we find that there is a value of waiting to invest, but its value appears not significantly related to our measure of industry and country uncertainty. In the analysis, we also controlled for several variables, and found that the expected profitability is positively related to the population size, the market power, the comparative advantage of the host country in its cost of labour, the average industry size and bilateral trade agreements.

In terms of future lines of research, recent papers (e.g. Lambrecht and Perraudin, 2003; Grenadier, 2002) show that sustained competition among firms reduces the value of the waiting option significantly. As erosion in the value of waiting leads to a lower trigger value while leaving the standard deviation unchanged (hence leading to earlier investments), the competition effect itself does not work directly through the standard deviation. On the contrary, we showed that the hazard rate may be an increasing function of uncertainty. As a result, to test the effect of competition, the function incorporating the trigger value should model not only the investment spell relative to the first TNC entering the market, but also the timing of further investments, explicitly including, in the functional form, a measure of competition, as in the previously quoted papers. We leave such a test for future research. However, we think that the estimation method proposed in this article can serve as a good starting point for further empirical work on this issue.

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References

Aiginger, K. (1987). *Production and Decision Theory under Uncertainty*, Blackwell, Oxford.

Altomonte, C. (2000). ‘Economic determinants and institutional frameworks: FDI in economies in transition’, *Transnational Corporations*, Vol. 9, pp. 75–106.

Bar-Ilan, A. and Strange, W. C. (1996). ‘Investment lags’, *American Economic Review*, Vol. 86, pp. 610–622.

Bekaert, G. and Harvey, C. R. (1997). ‘Emerging equity market volatility’, *Journal of Financial Economics*, Vol. 43, pp. 29–77.

Brunetti, A. and Weder, B. (1998). ‘Investment and institutional uncertainty: a comparative study of different uncertainty measures’, *Weltwirtschafliches Archiv*, Vol. 134, pp. 513–533.

Campa, J. M. (1993). ‘Entry by foreign firms under exchange rate uncertainty’, *Review of Economics and Statistics*, Vol. 75, pp. 614–622.

Carstensen, K. and Toubal, F. (2004). ‘Foreign direct investment in Central and Eastern European countries. A dynamic panel analysis’, *Journal of Comparative Economics*, Vol. 32, pp. 3–22.

Darby, J., Hughes Hallett, A., Ireland, J. and Piscitelli, L. (1999). ‘The impact of exchange rate variability on the level of investment’, *Economic Journal*, Vol. 109, pp. 55–67.

Davies, S. and Lyons, B. (1996). *Industrial Organization in the European Union*, Clarendon Press, London.

De Santis, G. and Imrohoroglu, S. (2000). 'Stock returns and volatility in emerging financial markets', *Journal of International Money and Finance*, Vol. 16, pp. 561–579.

Dixit, A. and Pindyck, R. (1994). *Investment Under Uncertainty*, Princeton University Press, Princeton.

Driver, C. and Moreton, D. (1991). 'The influence of uncertainty on UK manufacturing investment', *Economic Journal*, Vol. 101, pp. 1452–1459.

Favero, C., Pesaran, H. and Sharma, S. (1994). 'A duration model of irreversible oil investment: theory and empirical evidence', *Journal of Applied Econometrics*, Vol. 9, pp. 95–112.

Fedderke, J. (2004). 'Investment in fixed capital stock: testing for the impact of sectoral and systematic uncertainty', *Oxford Bulletin of Economics and Statistics*, Vol. 66, pp. 165–187.

Ferderer, J. (1993). 'The impact of uncertainty on aggregate investment spending: an empirical analysis', *Journal of Money, Credit, and Banking*, Vol. 25, pp. 30–48.

Garcia Blandon, J. (2001). 'The timing of foreign direct investment under uncertainty: evidence from the Spanish banking sector', *Journal of Economic Behavior and Organization*, Vol. 45, pp. 213–224.

Geroski, P. A. (1991). *Market Dynamics and Entry*, Blackwell, Oxford.

Ghosal, V. and Loungani, P. (2000). 'The differential impact of uncertainty on investment in small and large businesses', *Review of Economics and Statistics*, Vol. 82, pp. 338–343.

Goldberg, L. (1993). 'Exchange rates and investment in United States industry', *Review of Economics and Statistics*, Vol. 75, pp. 575–588.

Grambsch, P. M. and Therneau, T. M. (1994). 'Proportional hazard tests and diagnostics based on weighted resudals', *Biometrika*, Vol. 81, pp. 515–526.

Greene, W. (1999). *Econometric Analysis*, 4th edn, Prentice-Hall, Englewood Cliffs, NJ.

Grenadier, S. R. (2002). 'Option exercise games: an application to the equilibrium investment strategies of Firms', *Review of Financial Studies*, Vol. 15, pp. 691–721.

Guiso, L. and Parigi, G. (1999). 'Investment and demand uncertainty', *Quarterly Journal of Economics*, Vol. 114, pp. 185–227.

Han Kim, E. and Singal, V. (2000). 'Stock market openings: experience at emerging economies', *Journal of Business*, Vol. 73, pp. 25–66.

Harchaoui, T. and Lasserre, P. (2001). 'Testing the option value of irreversible investment', *International Economic Review*, Vol. 42, pp. 141–166.

Holland, D. and Pain, N. (1998). *The Diffusion of Innovations in Central and Eastern Europe. A Study of the Determinant and Impact of Foreign Direct Investment*, Discussion Paper No. 137, NIESR, London.

Huizinga, J. (1993). 'Inflation uncertainty, relative price uncertainty, and investment in U.S. manufacturing', *Journal of Money, Credit, and Banking*, Vol. 25, pp. 521–549.

Hurn, A. and Wright, R. (1994). 'Geology or economics? Testing models of irreversible investment using North Sea oil data', *Economic Journal*, Vol. 104, pp. 363–371.

Kiefer, N. (1988). 'Economic duration data and hazard functions', *Journal of Economic Literature*, Vol. 26, pp. 646–679.

Kogut, B. and Chang, S. J. (1996). 'Platform investments and volatile exchange rates: direct investment in the U.S. by Japanese electronics companies', *Review of Economics and Statistics*, Vol. 78, pp. 221–231.

Lambrecht, B. and Perraudin, W. (2003). 'Real options and preemption under incomplete information', *Journal of Economic Dynamics and Control*, Vol. 27, pp. 619–643.

Leahy, J. and Whited, T. (1996). 'The effect of uncertainty on investment: some stylized facts', *Journal of Money, Credit and Banking*, Vol. 28, pp. 64–83.

Lensink, R. (2002). 'Is the uncertainty–investment link non-linear? Empirical evidence for developed economies', *Weltwirtschaftliches Archiv*, Vol. 138, pp. 131–147.
Pagan, A. and Vella, F. (1989). 'Diagnostic tests for models based on individual data: a survey', *Journal of Applied Econometrics*, Vol. 4, pp. S29–S59.
Patillo, C. (1998). 'Investment, uncertainty, and irreversibility in Ghana', *IMF Staff Papers*, Vol. 45, pp. 522–553.
Sarkar, S. (2000). 'On the investment–uncertainty relationship in a real options model', *Journal of Economic Dynamics and Control*, Vol. 24, pp. 219–225.
Servén, L. (2003). 'Real exchange rate uncertainty and private investment in LDCs', *Review of Economics and Statistics*, Vol. 85, pp. 212–217.
Sinn, H. W. and Weichenrieder, A. J. (1997). 'Foreign direct investment, political resentment and the privatization process in Eastern Europe', *Economic Policy*, Vol. 24, pp. 179–210.
Tan, B. and Vertinsky, I. (1996). 'Foreign direct investment by Japanese electronics firms in the United States and Canada: modelling the timing of entry', *Journal of International Business Studies*, Vol. 27, pp. 655–681.

Appendix

Data description

The model includes a total of 48 NACE 2 and 3 digits industries, grouped as follows.

No advertizing and no R&D – low sunk costs. 10–14 (mining of coal, metals and stone; extraction of petroleum and natural gas); 151 and 152 (production and transformation of meat and fish); 156 (grains); 158 (fabrication of bread, tea, coffee and other alimentary products); 17 (textiles); 18 (clothing); 19 (leather); 20 (wood); 21 (paper and pulp); 22 (publishing and press); 252 and 262 (plastics and ceramics); 26 (other non-metallic products); 27 (metallurgy); 28 (metals); 292 (general machinery); 351 (ship building); 361 and 362 (furniture); 366 (other general manufacturing).

Advertizing intensive – medium sunk costs. 153 and 155 (vegetables, milk and dairy products); 157 (pet food); 159 (drink and beverages); 16 (tobacco); 363 and 365 (musical instruments and toys).

R&D intensive – medium sunk costs. 241 and 242 (basic chemicals and agrochemicals); 246 and 247 (other chemical products and synthetic fibres); 251 (rubber products); 291 (mechanical machinery); 294 and 295 (machine tools); 30 (office machines); 31 (electrical appliances, excluding domestic); 321 (electronics); 331 and 332 (medical and precision instruments); 343 (car components); 352 and 354 (railways; motorcycles).

Advertizing and R&D intensive – high sunk costs. 243, 244 and 245 (paintings, pharmaceuticals and soaps and detergents); 293 (agricultural machines); 297 (domestic appliances); 322 and 323 (communication equipment); 334 and 335 (optics, photography, clocks); 341 (car production); 401 and 402 (electricity and gas); 642 (telecommunications).

Services – medium sunk costs. 45 (construction); 55 (hotels and restaurants); 65 and 66 (financial intermediation and insurance); 72 (computer and related activities); 73 (research and development); 92 (cultural and sporting activities).

Data refer to the following *countries*: Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia.

The source of macroeconomic data is the WIIW Database on Eastern Europe (http://www.wiiw.ac.at), 1990–2001. Other data derive from the AMADEUS data set. The variables employed are the following:

- gdppc: per capita Gross Domestic Product in US$ of the countries considered
- pop: population in thousands of the countries considered
- dist: distance in km from each country's capital city and an 'average' European location, chosen as the city of Frankfurt
- relwage: inverse of the average monthly gross wage of each country with respect to the average of the countries considered
- indsize: share of each industry considered in each country gross value-added
- MESdom: median domestic firm's employment of each industry calculated on the set of considered countries
- lib: an index with a scale from 1 to 5 representing the method of privatization, where 1 is the most impeding method for TNCs (vouchers) and 5 is the most favourable (sales to outside owners only). See Carstensen and Toubal (2004) for further details.

For Tables 1 and 2, the *year* in which each variable has been measured is 1990, while variables are time dependent for Table 3. The EU-FTA and CEEC-FTA dummies take value 1 if in the considered year a bilateral free-trade agreement has been signed, respectively, with the EU (Europe agreement) or with other CEECs (CEFTA), according to the following table.

Country	*Signature of Europe Agreement*	*Membership of CEFTA*
Bulgaria	1 March 1993	1 January 1999
Czech Republic	6 October 1993	21 December 1992
Hungary	16 December 1991	21 December 1992
Poland	16 December 1991	21 December 1992
Romania	8 February 1993	1 July 1997
Slovakia	6 October 1993	21 December 1992
Slovenia	10 June 1996	1 January 1996