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Investment Decisions in Manufacturing: Assessing the Effects of Real Oil Prices and their Uncertainty

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Abstract

We investigate the effects of real oil prices and their uncertainty on the investment decision.

1 Introduction

Disaggregate investment decisions are largely characterized by persistent and non-smooth behavior, i.e. prolonged periods during which investment is actually zero are followed by prolonged periods in which investment is positive (Caballero *et al.* 1995; Doms and Dunne 1998; Nilsen and Schiantarelli 2003).

ment, we separate investment decisions between activity (either positive or negative investment) and inactivity (zero investment episodes).

Our analysis has a number of novel and distinct features. *First*, we make use of plant-level data to analyze the effects of real oil prices on investment, whereas existing studies operate at a higher level of aggregation.[3] *Second*, we explicitly evaluate the existence and the direction of the effects of real oil prices and real oil-price uncertainty on the dynamics of the investment decision process, which – to the best of our knowledge – have not been explored before at such a disaggregate level.[4] *Third*, we do so by using dynamic binary choice models of investment behavior that disentangle the effect of real oil prices and their uncertainty from persistence due to unobserved heterogeneity or state dependence.

Our findings show that increases in real oil price changes and real oil price uncertainty adversely affect investment decisions of manufacturing plants. In some more detail, we find that rising real oil prices significantly reduce the probability of investment action. This finding is robust across different estimators employed. Additionally, we find that increases in real oil price uncertainty raise significantly the probability of investment inaction. This finding is robust not only across estimators, but also when employing different measures of uncertainty such as the one-sided 'risk' measures suggested by Kilian and Manganelli (2007).

Moreover, in one set of robustness experiments we allow for the effect of the unexpected real oil price change (a 'shock') and find that it reduces significantly the probability of investment. That is we find that there are significantly negative *level* effects from unexpected changes in real oil prices, without making the adverse effects of increases in real oil price uncertainty less important. This piece of evidence can be considered as complementary to those in Edelstein and Kilian (2007), who show, however, that there is no empirical support for theoretical models of the effects of uncertainty on business fixed investment expenditures.[5] Our results show that there are indeed strong uncertainty

[3] The use of a micro-level panel dataset is essential to avoid the problem of aggregation over production units, which results when investment decisions are observed at a higher aggregation level that masks investment discontinuity. The use of such a dataset makes it more likely that zeros (investment inaction) will be observed.

[4]

effects on investment dynamics, but they are discernible at a more disaggregate level of analysis.

Finally, as a by-product of our analysis, we document the existence of strong state-dependence in investment. We find that estimates of state dependence in investment are affected, as expected, by the assumptions made regarding initial conditions and the treatment of unobserved heterogeneity. Despite the sensitivity to these assumptions, we find that the likelihood of investment action is significantly positively correlated with investment action in the last period, across all estimators examined.

The rest of the paper is organized as follows. Section 2 describes our econometric methodology for modeling the investment process and for measuring real oil price uncertainty. Section 3 gives a brief overview of the data employed, discusses our core empirical findings as well as various extensions and robustness experiments, while section 4 concludes.

2 Empirical Methodology

In our work we make use of dynamic random-effects models to model the probability of investment action, which include the previous state to allow for state dependence. Special attention is paid to the treatment of unobserved heterogeneity and initial conditions. The former relates to whether the observed persistence of investment is the outcome of 'pure' or 'spurious' state dependence.[6] The initial conditions are important, as in short panels, like ours, they have an impact on the entire path of outcomes.

The empirical specification for modeling the investment decision takes the form of a dynamic binary choice model

$$y_{it} = \quad \{\ {}_{it}^{0}\ \ + \ y_{it\ 1} + c_i + u_{it} > 0\}; \quad i = 1; \ldots; N; \ t = 1; \ldots; T_i; \tag{1}$$

where y_{it} is an binary indicator variable for investment action by plant $i = 1; \ldots; N$ in year t, the vector ${}_{it}$ contains explanatory variables affecting the propensity to trigger investment, while c_i denotes a time-invariant component capturing plant-specific heterogeneity and u_{it} is a well-behaved random term.

The random-effects (RE) specifications we employ, require that the distributional properties of c_i and u_{it}, as well as their relationship to the explanatory variables be specified, along with the initial

[6]Pure state dependence would imply that the probability of investment in year t depends on the outcome in year t , after controlling for unobserved heterogeneity.

conditions of the dynamic process. In what follows we assume that x_{it} is strictly exogenous for u_{it} (conditional on c_i), and more specifically that $u_{it}|\mathbf{X}, \mathbf{c} \sim \mathrm{NIID}(0, \sigma_u^2)$.[7] The standard random-effects model assumes that $c_i|\mathbf{x}_i \sim \mathrm{NIID}(0, \sigma_c^2)$. An alternative following Mundlak (1978) and Chamberlain (1984) is to allow for correlation between c_i and the observed characteristics, assuming a relationship of the form $c_i = \bar{\mathbf{x}}_i'\mathbf{a} + \alpha_i$, with $\alpha_i \sim \mathrm{NIID}(0, \sigma_\alpha^2)$ being independent of $\mathbf{x}_{it}$ and u_{it} for all i and t and $\bar{\mathbf{x}}_i \equiv T_i^{-1}\sum_{t=1}^{T}\mathbf{x}_{it}$ – the correlated random effects (CRE) model. In this instance, model (1) may be written as

$$y_{it} = 1\{\mathbf{x}_{it}'\boldsymbol{\beta} + \gamma y_{it-1} + \bar{\mathbf{x}}_i'\mathbf{a} + \alpha_i + u_{it} > 0\}; \quad i = 1, \ldots, N; \; t = 1, \ldots, T_i. \tag{2}$$

The random-effects specification (2) implies that the correlation between the composite error $v_{it} = \alpha_i + u_{it}$ in any two periods will be the same, namely $\lambda = \mathrm{corr}(v_{it}, v_{is}) = \sigma_\alpha^2/(\sigma_\alpha^2 + \sigma_u^2)$ for $t, s = 1, \ldots, T_i$ and $t \neq s$. Moreover, since y is binary, a convenient normalization is $\sigma_u^2 = 1$. If $\gamma = 0$, model (2) involves only a single integral, by conditioning on the individual effect and integrating it out, so parameters can be estimated by Maximum Likelihood (ML) using Gaussian–Hermite quadrature (Butler and Moffitt 1982).

In order to estimate the model when $\gamma \neq 0$, it is necessary to make an assumption about the relationship between the initial observation, y_{i0}, and the individual-specific effect. One possibility is to assume that y_{i0} is exogenous, i.e. a nonrandom starting position for each i. In this case, likelihood can be decomposed into two independent factors and the joint probability for $t = 1, \ldots, T_i$, and can be maximized without reference to that for $t = 0$. However, if the initial conditions are correlated with α_i, this method of estimation overstates state dependence (Chay and Hyslop 2000).

In our work we explore two alternative approaches that treat the initial observations as endogenous following Heckman (1981) and Wooldridge (2005) respectively.[8] Heckman (1981) suggests specifying a linearized reduced-form equation for the initial value:

$$y_{i0} = 1\{\mathbf{z}_{i0}'\boldsymbol{\pi} + \theta\alpha_i + u_{i0} > 0\} \tag{3}$$

where $\mathbf{z}_{i0} = (\mathbf{x}_{i0}', \bar{\mathbf{x}}_i')'$ and u_{i0} is assumed to be independent of α_i, with the former satisfying the same distributional assumptions as u_{it} for $t \geq 1$. A test of $\theta = 0$ provides a test of exogeneity of the

[7] Here $\mathbf{c} \equiv (c_1, \ldots, c_N)'$ and $\mathbf{X} \equiv (\mathbf{x}_1', \ldots, \mathbf{x}_N')'$ with $\mathbf{x}_i \equiv (\mathbf{x}_{i1}, \ldots, \mathbf{x}_{iT_i})'$.

initial condition in this model.

Equations (2) and (3) together specify a complete model for a random sample $(y_0; y_1; :::; y_T)$. One can then marginalize the likelihood with respect to $_i$, obtaining the appropriate likelihood function for the maximization. For instance, the contribution to the likelihood for plant i in the model is given by

$$L_i = \quad [({}^0_{i0} \quad + \quad _i)(2y_{i0} \quad 1)] \prod_{t=1}^{T_i} [({}^0_{it} \quad + \ y_{it \ 1} + \ {}^0_i \quad + \quad _i)(2y_{it} \quad 1)] \ d \ (\ _i); \qquad (4)$$

where is the standard normal cumulative distribution function. As $_i$ is normally distributed, the above integral can be evaluated using Gaussian–Hermite quadrature (Butler and Moffitt 1982).

A different approach to the initial conditions problem is proposed by Wooldridge (2005), who suggests a Conditional Maximum Likelihood (CML) estimator, considering the distribution conditional on the initial period value and exogenous covariates. More specifically, instead of specifying a model for y_{i0} given $_i$ and $_i$, a model is specified for $_i$ given $_i$ and y_{i0}. In particular it is assumed that

$$_i = \ _0 + \ _1 y_{i0} + a_i; \qquad (5)$$

as the Mundlak specification above already includes $_i$. Substituting into (2) gives

$$y_{it} = \ f \ {}^0_{it} \ + \ y_{it \ 1} + \ _0 + \ _1 y_{i0} + \ {}^0_i \ + a_i + u_{it} > 0g; \quad i = 1; :::; N; \ t = 1; :::; T_i: \qquad (6)$$

In this model, the contribution to the likelihood function for individual i is given by

$$L_i = \prod_{t=1}^{T_i} [({}^0_{it} \ + \ y_{it \ 1} + \ _0 + \ _1 y_{i0} + \ {}^0_i \ + a_i)(2y_{it} \quad 1)] \ d \ (a_i); \qquad (7)$$

where is the normal distribution function of the new unobservable individual-specific heterogeneity a_i given in (5). So (6) is again a one factor probit model that can be easily estimated my ML using Gaussian quadrature procedures. In Wthath155(sres.)-method50(c9)25(w)-2.c25(wTJ -4)-2wudi(of)-22wGaussia where T_{ij} is the number of common time series observations available for any pair of plants i and j, and $\hat{\rho}_{ij}$ is the correlation coefficient computed using the generalized residuals estimated under the null hypothesis. They show that under the null hypothesis of cross-sectional independence, $CD \xrightarrow{d} N(0,1)$ for $N, T \to \infty$ and that the CD statistic has exactly mean at zero for fixed values of N and T, under a wide range of panel data models, including heterogeneous models, non-stationary and dynamic panels.

3 Data and Empirical Findings

3.1 Data and Benchmark Measure of Real Oil-Price Uncertainty

Moreover, we find strong evidence of endogeneity of the initial conditions, which turn out to be strong determinants of the subsequent investment decision process. In particular, looking at the results from both the Heckman and Wooldridge estimators, we reject the null hypothesis of exogeneity of initial conditions – as for the former and the marginal effect of $y_{i;0}$ for the latter are strongly significant.

Examining the issue of state dependence, across all four specifications the lagged investment activity variable is highly significant, reflecting strong persistence. We find that the size of the relevant estimated marginal effect decreases somewhat when we take into account heterogeneity and especially when initial conditions are treated as endogenous. In addition, there are a number of ways in which the partial effect of $y_{it\ 1}$ on $\Pr(y_{it} = 1)$ may be assessed in models like the ones considered here. The approach we take is based on estimates of counterfactual outclly tating instance, focusing on the last column of Table 1, we find that an increase of real oil prices by one percentage point reduces the probability of investment action by 0.07 percent. *Second*, we also find that an increase in real oil price uncertainty, reduces significantly the probability of investment action, irrespectively of the estimator employed. For example, focusing again on the last column of Table 1, we find that an increase in our measure of real oil price uncertainty by 0.01 (roughly 11% relative to its average value) reduces the probability of investment action by 0.46 percent.[11] Moreover, even when allowing for unobserved heterogeneity to be correlated with observable characteristics, as well as explicitly modeling initial conditions, increases in real oil prices and real oil price uncertainty retain their negative effect on the probability of investment activity. More importantly, though, we see that the estimated magnitude of these effects is robust across all estimators employed.

Finally, we evaluate the extent to which the assumption of cross-sectional independence of the error term is valid, by means of the CD-test. For all four estimators, we find that the null is strongly rejected. In addition, the estimated average cross-sectional correlation of the generalized residuals is above 0.34. However, there is no well-established technique that allows us to correct for this deviation from the IID assumption.[12] To this end, our results should be interpreted, keeping this caveat in mind.

3.3 Extensions and Sensitivity Analysis

In this subsection we examine various extensions, such as using different measures of real oil–price uncertainty, assessing the existence of asymmetry of oil–related effects, and expanding the set of controls to include plant-specific uncertainty, the business–cycle and industry–wide uncertainty.[13]

3.3.1 Alternative Measures of Real Oil Price Uncertainty

Thus far, we have employed a measure of real oil–price uncertainty that is derived from a GARCH model of conditional volatility, which despite being based on out-of-sample forecasts over a one–year horizon, might not fully capture the 'risk' a decision maker is facing. On the one hand, this measure converges quickly to the unconditional volatility of real oil prices (Kilian and Vigfusson 2011), and

[11] To understand better the magnitude of these effects, note that an increase of sales by 1% of value added increases the probability of investment action by 0.15%!

[12] We have already included time-effects as the least possible remedy for the existence of cross-sectional dependence.

[13] We briefly discuss results when using alternative measures of uncertainty/risk. The rest of our estimation results are available in an online supplement.

on the other hand, in the context of investment decisions, the risk of real oil price increases rather than a simple increase in variance of real oil prices, is probably more relevant.

In deriving such one–sided 'risk' measures we have two options. The first is to follow Kilian and Manganelli (2007) and define the 'risk' of excessive real oil price increase h periods from date t, above a specific threshold value, ξ, as

$$EIR_{\alpha}(\xi) = \int_{\xi}^{+\infty} (\pi_{t+h} - \xi)^{\alpha}\, dF(\pi_{t+h}); \tag{9}$$

where $F(\cdot)$ is the probability distribution function of future real oil–price change outcomes (π_{t+h}), estimated by the empirical distribution of real oil–price changes forecasts. Note that this class of risk measures is defined in terms of percentage increases in real oil prices, which squares well with standard financial planning models and practice (Ross *et al.* 2005). In such models, one usually employs forecasts of the growth rates of all the relevant variables (such as sales, cost etc.) as inputs, so risk measures like (9) seem more appropriate. The second, which is more conventional in the economics literature, is to define the risk measures in terms of the real oil price (the relative price of oil) as this would show up in many standard profit maximization problems. In this instance, we may define the 'upside risk' that real oil prices h periods from date t, R_{t+h}, will be above a threshold value, $\bar{R}$, as

$$UR_{\alpha}(\bar{R}) = \int_{\bar{R}}^{+\infty} \left(R_{t+h} - \bar{R}\right)^{\alpha} dF(R_{t+h}); \tag{10}$$

where $F(\cdot)$ is the predictive distribution of real oil prices. As both these classes of risk measures are useful in different contexts, we report results for both.

Before proceeding note that for $\alpha = 1$ both (9) and (10) reduce to tail conditional expectations, multiplied by the corresponding tail probabilities: $EIR_1(\xi) = \mathrm{E}(\pi_{t+h} - \xi \mid \pi_{t+h} > \xi)\Pr(\pi_{t+h} > \xi)$ and $UR_1(\bar{R}) = \mathrm{E}\left(R_{t+h} - \bar{R} \mid R_{t+h} > \bar{R}\right)\Pr\left(R_{t+h} > \bar{R}\right)$; while for $\alpha = 2$ these reduce to the (one-sided) variance about the target again multiplied by the corresponding tail probability: $EIR_2(\xi) = \mathrm{E}[(\pi_{t+h} - \xi)^2 \mid \pi_{t+h} > \xi]\Pr(\pi_{t+h} > \xi)$ and $UR_2(\bar{R}) = \mathrm{E}[(R_{t+h} - \bar{R})^2 \mid R_{t+h} > \bar{R}]\Pr\left(R_{t+h} > \bar{R}\right)$. The excessive increase risk measures (EIR) can be computed as in Kilian and Manganelli (2007), and the upside risk measures (UR) can be calculated as discussed in Alquist *et al.* (2011), for different values of α. In calculating such risk measures we have chosen ξ to be 20% and $\bar{R}$ to be 50 euros (in constant 2005 prices) – our results not being sensitive to this choice – and focus at a four-years ahead horizon. Albeit limited in nature, as many business fixed investment projects tend to have lifetimes well beyond four years, this choice is intended to capture – to the extent that is possible – that the relevant measure of risk should reflect the life-time of the investment project.

Table 2 summarizes the estimated marginal effects from employing the dynamic CRE estimators of Heckman and Wooldridge and these one-sided risk measures, leaving the rest of the controls the same. When examining real oil prices, we see that their estimated marginal effects are closely in-line with those reported in Table 1 and significant. One exception is when we employ the Heckman estimator and the $\boldsymbol{UR}$ measures of one-sided risk: In this case increases in real oil prices do not influence insignificantly the probability of investment.[14]

[Insert Table 2 About Here.]

On the other hand, when we employ the $\boldsymbol{EIR}_1$ or the $\boldsymbol{EIR}_2$ measures, we find that any increase in these translates in a significantly lower probability of investment action. Instead, when we employ the $\boldsymbol{UR}$ measures, we again find that the probability of investment is lowered, but not in a significant

creases when output rises above trend-output (the economy is in a boom), whereas it is less likely that investment will take place when output is cyclically below trend (in a recession).

Finally, we evaluate whether the inclusion of industry-wide uncertainty in our controls, makes a significant difference to our results. To measure industry uncertainty we follow Bloom *et al.* (2007) and use the unconditional standard deviation of daily stock returns from the Industrials Price Index, in year t

smaller plants, whereas no such evidence is found for real oil prices.

Finally, we document the existence of strong state-dependence in investment. We find that estimates of state dependence in investment are affected by the assumption made regarding initial conditions and the treatment of unobserved heterogeneity. Despite the sensitivity to these assumptions, we find that likelihood of triggering investment is significantly positively correlated with investment action in the last period, suggesting that its presence significantly affects the time trajectory of investment decisions.

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Table 1: Dynamic Models of Investment Activity

Covariate	Dynamic RE (Exogenous Initial Conditions)	Dynamic CRE (Exogenous Initial Conditions)	Dynamic CRE (Endogenous Initial Conditions)	
			Heckman	Wooldridge
$y_{i;t-1}$	0.330***	0.314***	0.194***	0.275***
	[35.611]	[33.796]	[23.509]	[30.902]
$\hat{}^{oil}_{t\|t-1}$	-0.749***	-0.500***	-0.454***	-0.460***-0.460***

Table 1 Continued

	Dynamic RE (Exogenous Initial Conditions)	Dynamic CRE (Exogenous Initial Conditions)	Dynamic CRE (Endogenous Initial Conditions)	
			Heckman	Wooldridge
Diagnostics				
	0.282***	0.256***	0.318***	0.259***
	[20.589]	[19.102]	[19.892]	[20.505]
$\log L$	-15812.196	-15478.078	-12717.619	-15275.266
N.Obs	42794	42794	47997	42794
CD-Test	612.352***	766.229***	797.184***	762.235***
r	0.342	0.358	0.363	0.359
Predicted probabilities				
Pred. Prob. p_0	0.412	0.386	0.419	0.366
Pred. Prob. p_1	0.925	0.934	0.947	0.938
APE = $p_1 \quad p_0$	0.512	0.547	0.528	0.572
PPR = $p_1 = p_0$	2.242	2.416	2.259	2.562

Notes for Table 1: The oil price uncertainty metric, $^{oil}_{t|t}\ _1$, is constructed as a twelve month average of the predicted *one-year-ahead* monthly real oil price volatility. $^{oil}_{t}$ denotes the percentage change of the real oil price in year t relative to year t . The set of controls also includes industry and time dummies. In the first two specifications the initial condition is taken to be exogenous, while $y_{i;0}$ denotes the initial condition, as in Wooldridge (2005). In the Heckman (1981) estimator, the initial period is modeled as a function of $SL_{i;\ 1}; CF_{i;\ 1}; EMP_{i;\ 1}$ and all time-averaged plant-specific characteristics. L in the Heckman (1981) estimator is for the joint model for all periods (1994-2005), whereas in all other models it corresponds to period 1995-2005, which also explains the difference in the number of observations. CD-test denotes the test of cross-sectional independence proposed by Hsiao *et al.* (2012), and r indicates the average pair-wise correlation coefficients of the generalized residuals. p_0 denotes the average predicted probability for investment action in year t, given inaction in the previ [- tear p ienotes the pverage predicted prebability for investment a

Table 2: Alternative Uncertainty/One-Sided Risk Measures

	Heckman	Wooldridge	Heckman	Wooldridge	Heckman	Wooldridge	Heckman	Wooldridge
	Risk Measure Employed							
Covariate	$\boldsymbol{EIR_{1t}^{0:20}}$							

Table 2 Continued

	Heckman	Wooldridge	Heckman	Wooldridge	Heckman	Wooldridge	Heckman	Wooldridge
	Risk Measure Employed							
	$EIR_{1t}^{0:20}$		$EIR_{2t}^{0:20}$		UR_{1t}		UR_{2t}	
Initial Conditions								
	1.019***		1.019***		1.019***		1.019***	
	[13.210]		13.210		13.210		13.210	
$y_{i;0}$		0.136***		0.136***		0.136***		0.136***
		[17.841]		17.841		17.841		17.841
Diagnostics								
	0.318***	0.259***	0.318***	0.259***	0.318***	0.259***	0.318***	0.259***
	[19.892]	[20.505]	[19.892]	[20.505]	[19.892]	[20.505]	[19.892]	[20.505]
L	-12717.619	-15275.266	-12717.619	-15275.266	-12717.619	-15275.266	-12717.619	-15275.266
N.Obs	47997	42794	47997	42794	47997	42794	47997	42794
CD-Test	797.184***	805.432***	797.184***	805.432***	797.184***	805.432***	797.184***	805.432***
r	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363
Predicted probabilities								
Pred. Prob. p_0	0.419	0.366	0.419	0.366	0.419	0.366	0.419	0.366
Pred. Prob. p_1	0.947	0.938	0.947	0.938	0.947	0.938	0.947	0.938
APE p_1 p_0	0.528	0.572	0.528	0.572	0.528	0.572	0.528	0.572
PPR p_1=p_0	2.259	2.562	2.259	2.562	2.259	2.562	2.259	2.562

Notes for Table 2: EIR