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To Buy or Not to Buy? Uncertainty, Irreversibility, and Heterogeneous Investment Dynamics in Italian Company Data

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This study tests for the presence of real options effects induced by uncertainty and (partial) irreversibility on fixed capital investment using Italian company data. Our approach recognizes that firm-level investment spending may, itself, be aggregated over multiple investment decisions in separate types of capital goods and emphasizes effects of uncertainty on short-run investment dynamics. Using a survey-based measure of uncertainty related to the assessment of managers responsible for the firms' investment plans, we find evidence of heterogeneous and nonlinear dynamics pointing to a slower adjustment of investment in response to demand shocks at higher levels of uncertainty. Our results also point to an additional source of nonlinearity originating from a convex response of investment to demand shocks. [JEL C23, D8, D92, E22]

Aggregate investment spending is an important source of fluctuations over the business cycle. A puzzling aspect of such fluctuations is that they sometimes occur in connection with relatively small shocks or policy impulses. Previous contributions on the "small-shocks, large-cycles" puzzle have focused on borrowers'

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credit-market conditions and their ability to propagate an initial real or monetary shock to the rest of the economy (Bernanke, Gertler, and Gilchrist, 1996 and 1998; and Hubbard, 1998).

This paper considers an alternative mechanism that may explain the observed large cyclical movements of investment with respect to the business cycle, based on firms' behavior under uncertainty. Important early contributions on the relationship between investment and uncertainty include those of Lucas and Prescott (1971), Hartman (1972), Nickell (1977a and 1977b), and Abel (1983). In the last decade, research has focused on a class of models in which real options influence investment behavior, because firms may have an incentive to wait for the arrival of new information, thus postponing the implementation of their investment plans (Bertola, 1988; Pindyck, 1988; Caballero, 1991; and Dixit and Pindyck, 1994; see also the survey by Carruth, Dickerson, and Henley, 2000).

Theoretical analyses have shown that the impact of uncertainty on the level of the capital stock in the long run is ambiguous in this class of models (Abel and Eberly, 1999; and Caballero, 1999). Perhaps for this reason, empirical studies have not reached any consensus on the sign or significance of this long-run relationship. However, more recent theoretical contributions have emphasized the effects of uncertainty on short-run investment dynamics (Abel and Eberly, 1999; and Bloom, 2000), and empirical studies have found evidence consistent with the predicted weaker response of investment to demand shocks at higher levels of uncertainty (Guiso and Parigi, 1999; and Bloom, Bond, and Van Reenen, 2003).

This paper extends this empirical research using data on Italian firms. Following Bloom, Bond, and Van Reenen (2003), we test for the nonlinear and heterogeneous investment dynamics predicted by models with partial irreversibility and uncertainty. An important difference is that we do not rely on a stock-returns measure of uncertainty. Like Guiso and Parigi (1999), we use a sample of firms that is representative of the Italian manufacturing sector, for which we can derive a measure of uncertainty from survey responses of the managers who are responsible for the firms' investment decisions. Exploiting the panel nature of our data set, we investigate the short-run effects of uncertainty on investment dynamics, thus extending the cross-sectional analysis of Guiso and Parigi (1999).

We find evidence of heterogeneity across firms in investment dynamics and, in particular, of a weaker effect of demand shocks on investment for firms facing higher uncertainty. Interestingly, our findings also point to an additional source of nonlinearity originating from a convex response of investment to positive demand shocks.

I. A Review of the Literature

Early contributions have shown that uncertainty may increase the value of the marginal unit of capital, thus leading to more capital accumulation. Hartman (1972) and Abel (1983) investigate the impact of uncertainty on capital accumulation by focusing on the investment behavior of a competitive firm with constant returns to scale and (symmetric) convex adjustment costs. Under these assumptions, the resulting profit function is convex in price and, therefore, a mean-preserving increase in price uncertainty raises the expected return on a marginal unit of capital. This Jensen's inequality effect suggests a positive relationship between uncertainty and investment.

Importantly, the (symmetric) convexity of adjustment costs rules out the possibility that investment expenditures may be subject to some degree of irreversibility, a feature first emphasized by Arrow (1968). When investment is completely irreversible, and future demand, cost conditions, and other relevant factors are uncertain, firms have an incentive to wait until more information becomes available. On the contrary, when a firm does invest "[i]t gives up the possibility of waiting for new information to arrive that might affect the desirability or timing of the expenditure; it cannot disinvest should market conditions change adversely" (Dixit and Pyndick, 1994, p. 6). In other words, the implementation of a given investment plan carries an opportunity cost equivalent to the exercise of a financial call option. The decision to exercise such an option is irreversible. In fact, although the holder may sell the asset at a later stage, he or she will not be able to recover the value of the option.

Caballero (1991) investigates the impact of uncertainty and irreversibility on investment, highlighting the role that different assumptions on the functional form of adjustment costs and on the degree of competition and returns to scale play in shaping the response of investment to uncertainty. Interestingly, Caballero shows that as we move away from the hypothesis of perfect competition and constant returns to scale toward an environment of imperfect competition or decreasing returns to scale, the response of investment to uncertainty tends to become negative. In this setting, Caballero also shows that the more asymmetric the functional form of adjustment costs is, the more negative the relationship between investment and uncertainty becomes.

However, Pindyck (1993) notes that Caballero's (1991) analysis treats the firm in isolation, describing the effect of a mean-preserving increase in the variance of price, which is exogenous to the firm. While individual firms' investment and production decisions depend on the price process, they also collectively generate that process. Hence, Pindyck analyzes the interactions between irreversibility and uncertainty at the industry level by making price and industry output endogenous, and shows that this further strengthens the negative relationship between uncertainty and investment. In fact, assuming an industrywide setting, the possibility of entry of new firms or the expansion of existing ones limits the amount by which price can increase following industrywide positive shocks. With (partial) irreversibility, however, there is no similar mechanism that prevents price from falling after negative shocks. This asymmetry acts as a disincentive to invest.

A number of the earlier theoretical models focused on onetime investment decisions, in which there is no distinction between the effect of uncertainty on the level of investment and on the level of the capital stock. An important recent contribution by Abel and Eberly (1999) considers repeated investment decisions and highlights the ambiguity of the long-run relationship between uncertainty and the average level of the capital stock. They analyze the interaction between the user-cost effect and the hangover effect on the long-run level of the capital stock. The former implies that firms may end up having less capital in the long run than in the absence of irreversibility and uncertainty, because the user cost relevant for investment under irreversibility would be higher than that in the standard case of costless reversibility. The latter effect accounts for the difficulties faced by firms in divesting capital during economic downturns caused by the irreversibility constraint. Accordingly, if the latter effect were to dominate, firms would end up having more capital on average in the long run compared with the frictionless case. Interestingly, Abel and Eberly characterize these opposing effects and show that in the long run either effect may dominate, depending on the values assigned to the parameters in the model.

Abel and Eberly (1999) and Bloom (2000) emphasize that, with partial irreversibility, a higher level of uncertainty implies both a higher-threshold required rate of return to justify positive investment and a lower-threshold required rate of return to justify disinvestment. Because the optimal investment policy is characterized by a wider distance between the two thresholds, this unambiguously reduces the probability of an investment action in response to a given exogenous demand shock. Bloom (2000) also shows that irreversibility and uncertainty induce richer short-term investment dynamics, with lagged responses to past demand shocks occurring when thresholds are eventually reached.

Cooper and Haltiwanger (2006) analyze the effects of various forms of adjustment costs on investment dynamics. Observing that, in their panel of U.S. manufacturing plants, inaction in investment activity is often followed by periods of intensive adjustment of the capital stock, they argue that nonconvex costs and irreversibilities may play a central role in investment decisions. They estimate a model of capital stock adjustment that incorporates a rich specification of adjustment costs. Their empirical results suggest that both convex and nonconvex adjustment cost components are required to explain the observed adjustment process.

Bloom, Bond, and Van Reenen (2003) elaborate on the implications of these previous studies for investment dynamics. They simulate firm-level data from a calibrated model in which firm investment is aggregated over a number of independent plants, which are subject to idiosyncratic plant-level productivity shocks as well as to a common firm-level demand shock. One implication of such aggregation is that zero-investment observations become rare at the firm level, although the presence of plants within the region of inaction continues to influence the firm-level investment series. Interestingly, their approach identifies robust empirical predictions on firm-level investment dynamics, which can be recovered after aggregation across multiple capital inputs as well as production plants within a firm.

Bloom, Bond, and Van Reenen (2003) emphasize the following predictions about firm-level investment, which are tested in our study. First, in the short run, firms facing a higher level of uncertainty should respond less following a given demand shock, because, according to this theoretical framework, higher uncertainty widens the region of inaction relevant for each investment decision. This captures the intuition that firms may have a greater incentive to adopt a more cautious policy and wait for the arrival of new information before implementing their investment projects and exercising real options. In addition, they note that there should also be a nonlinear effect of demand shocks on investment spending in a setting in which firms invest at multiple plants or in multiple lines of capital. Typically, following a positive demand shock, the line of capital closest to the investment threshold starts adjusting, thus increasing the marginal productivity of the other lines of capital if one assumes supermodularity in the production functions.[1] As a result, other lines of capital may enter the investment region, therefore reinforcing the initial response of the firm to the demand shock. This process generates a strictly convex response to larger positive demand shocks. In principle, this process operates symmetrically following a negative shock, implying a strictly concave response to negative demand shocks that induce disinvestment. However, given that as a result of both depreciation and growth we tend to observe positive investment much more commonly than disinvestment, Bloom, Bond, and Van Reenen conclude that the dominant pattern is likely to be a convex response to demand shocks.

Among other notable empirical studies, Guiso and Parigi (1999) investigate the relationship between investment and uncertainty using data from a cross-sectional survey representative of the Italian manufacturing sector. In this survey, managers were asked to report their assessments of the distribution of future demand growth for their products. Guiso and Parigi use this to construct a firm-level measure of uncertainty that is closely related to the concept of demand uncertainty used in many theoretical models. They test a number of the theoretical predictions of the real options literature by comparing the investment behavior of firms with different degrees of market power and factor substitutability, access to credit markets, and liquidity constraints. Their evidence supports a negative relationship between uncertainty and investment, although their cross-sectional data set limits their ability to study the impact on investment dynamics.

Pattillo (1998) investigates the effect of uncertainty on the investment behavior of a short panel of Ghanaian manufacturing firms. Like Guiso and Parigi (1999), Pattillo constructs a direct measure of the owners' perceptions of uncertainty, using the variance of expected demand as a measure of uncertainty. Her findings also suggest that uncertainty has a negative effect on investment levels.

Other studies have investigated the impact of uncertainty using longer panel data sets. Ghosal and Loungani (1996), for instance, estimated the effect of price uncertainty on investment using a panel of U.S. manufacturing industries. For industries with lower seller concentration, thus likely to be highly competitive, the impact is negative and statistically significant, which is broadly consistent with models of irreversible capital investment; for industries characterized by imperfect competition, the impact is small and statistically insignificant.

II. Econometric Specifications of Investment Behavior

A Baseline Dynamic Model

The error-correction model, which allows for flexible adjustment of the capital stock toward its long-run equilibrium value, is a commonly used specification for estimating reduced-form empirical investment equations. In the absence of a convincing structural investment equation, this provides a useful benchmark for testing the null hypothesis of no effects of uncertainty on investment.

[1]The supermodularity of a production function $F(K_1, K_2, \ldots, K_N)$ is defined such that $\partial F(K_1, K_2, \ldots, K_N)/\partial K_i$ is increasing in all K_j, $j \neq i$. See Dixit (1997).

Consider the simplest model with no uncertainty, investment irreversibility, or other adjustment costs, and define k^*_{it} as the optimal, frictionless level of the logarithm of the capital stock for firm *i* in period *t*. Then, by defining y_{it} as the logarithm of real output, we can write the optimal capital stock as a function of a quantity variable:

$$k^*_{it} = a_i + \mu_t + y_{it}, \tag{1}$$

where a_i and μ_t are unobserved firm- and time-specific effects reflecting variation across firms and over time in the user cost of capital. It can be shown that this expression for the level of capital represents the solution to the static profit-maximization problem of a firm operating with a constant elasticity of substitution technology and constant returns to scale; if the production function is Cobb-Douglas, then equation (1) does not require the restriction of constant returns to scale (see, for example, Bond and Van Reenen, forthcoming).

Under partial irreversibility, the logarithm of the actual capital stock (k_{it}) and the hypothetical frictionless optimum (k^*_{it}) may differ and need not be equal on average in the long run. In this setting, we can exploit a result of Bloom (2000) according to which the long-run *growth rate* of a firm's actual capital stock under partial irreversibility and its hypothetical value under costless reversibility will be equal. Assuming that k^*_{it} is nonstationary, this implies that k_{it} and k^*_{it} are cointegrated, so that

$$k_{it} = k^*_{it} + \varphi_{it}, \tag{2}$$

with φ_{it} a stationary error term. This relation does not impose the restriction that φ_{it} should be a mean-zero process, because the average levels of these two notions of the capital stock may be different.

This relation can be exploited by specifying a dynamic error-correction relationship in which the actual capital stock k_{it} adjusts in the long run toward a target based on the hypothetical frictionless level k^*_{it}. Then, by substituting observed log output y_{it} for k^*_{it} using equation (1), we obtain a baseline empirical specification of the following form:

$$\Delta k_{it} = \alpha_t + \omega_0\, \Delta k_{i,t-1} + \omega_1\, \Delta y_{it} + \omega_2\, \Delta y_{i,t-1} + \theta\,(k-y)_{i,t-2} + \nu\, y_{i,t-2} + \eta_i + \varepsilon_{it}. \tag{3}$$

This type of model was introduced into the investment literature by Bean (1981). It can allow for rich short-run dynamics and incorporates a feedback mechanism toward the long-run target along the same lines as that proposed by Davidson and others (1978) and Hendry (1979).[2] Bloom, Bond, and Van Reenen (2003) show using simulated investment data that the adjustment dynamics generated by irreversibility and aggregation can be approximated by reduced-form econometric specifications of this type.

[2]For applications to microdata, see, for example, Bond, Harhoff, and Van Reenen (1999); Mairesse, Hall, and Mulkay (1999); and Bond and others (2003).

An Augmented Error-Correction Model

Following Bloom, Bond, and Van Reenen (2003), our specification tests for the nonlinear response of investment rates to demand shocks predicted by the partial irreversibility model by including an additional quadratic term in output growth $(\Delta y_{it})^2$. A positive coefficient on this term would be consistent with larger demand shocks having reinforcing effects on investment decisions in different types of capital or at different plants.

Our specification tests for the predicted effect of uncertainty on the short-run response of investment rates to demand shocks by including an additional interaction term $(\sigma_{it}\,\Delta y_{it})$, where σ_{it} is a measure of the uncertainty faced by firm i at time t. A negative coefficient on this term would be consistent with demand shocks having a weaker effect on investment at higher levels of uncertainty.

These additional terms, together with the approximation that $\Delta k_{it} \approx I_{it}/K_{i,t-1}-\delta_i$, where δ_i is a firm-specific depreciation rate, suggest an econometric model of investment rate of the following form:

$$(I_{it}/K_{i,t-1}) = \alpha_t + \omega_0(I_{i,t-1}/K_{i,t-2}) + \omega_1\,\Delta y_{it} + \omega_2\,\Delta y_{i,t-1} + \omega_3(\Delta y_{it})^2 + \omega_4(\sigma_{it}\,\Delta y_{it})$$
$$+\,\theta\,(k-y)_{i,t-2} + \nu y_{i,t-2} + \omega_5\sigma_{i,t-1} + \omega_6(C_{it}/K_{i,t-1}) + \eta_i + \varepsilon_{it}, \qquad (4)$$

where I_{it} is gross investment of firm i at time t, and K_{it} is its capital stock at the end of period t. As noted above, the analysis of investment under uncertainty with partial irreversibility suggests $\omega_4 < 0$ and, for firms undertaking positive investment, $\omega_3 > 0$. Our specification also allows for a possible long-run effect of uncertainty $(\sigma_{i,t-1})$ on the level of the capital stock, so that such a long-run effect would not be picked up by the interaction term $(\sigma_{it}\,\Delta y_{it})$.

To allow for a possible interaction between the real and financial decisions of firms, the ratio of cash flow to the beginning-of-period capital stock $(C_{it}/K_{i,t-1})$ is also included in the model, along the lines suggested by previous studies (see, for example, Hubbard, 1998; and Bond and Van Reenen, forthcoming). Although this is not the main focus of our paper, we control for cash flow to avoid the possibility that any effect of uncertainty on investment that we identify may simply be proxying for omitted liquidity effects.

In the specification above, the parameter θ represents the speed of adjustment through which the investment rate responds to a disequilibrium in the long-run relationship between capital and output. A negative value of the parameter θ is required for the estimated dynamics to be consistent with "error-correcting" behavior, so that a capital stock above (below) its desired level is associated with lower (greater) future investment. The parameter ν allows for the possibility that the long-run elasticity of capital with respect to output is different from unity.

Finally, in the error structure of equation (4), ε_{it} contains the residual component of φ_{it} in equation (2) that is not captured by the dynamic specification of equation (4). The unobserved firm-specific effects (η_i) allow for variation across firms in the price elasticity of product demand, the rate of depreciation, and more generally in the user cost of capital (a_i). The time dummies (α_t) allow for variation over time in the user cost of capital (μ_t), and allow for other aggregate shocks whose effects on investment are common to all firms. The inclusion of time dummies addresses concerns about spurious correlation between investment and uncertainty that may arise from fluctuations in measured uncertainty over the business cycle.

III. Data Description

Stylized Facts

The data set we use comes from the high-quality Survey of Investment in Manufacturing (SIM) conducted annually by the Bank of Italy. The data cover a random sample of firms representative of the Italian manufacturing sector from 1984 to 1998.[3]

The median firm size (266 employees) is relatively small, and 51 percent of the firms in the sample employ between 100 and 499 employees. Most firms belong to industrial holdings, while only a tiny proportion of them is quoted on the stock market in the years when such information is available.[4]

To investigate investment dynamics at the microlevel, we have merged the information from this source with that from a balance-sheet database.[5] Matching this additional information entails the loss of approximately one-third of the initial 14,873 observations. Furthermore, we drop all observations related to state-owned firms and restrict the sample to those firms for which we have at least four consecutive years of data, after constructing the appropriate lagged variables required for the empirical analysis. In Appendix Table A.1, we compare the resulting usable sample with the original survey data. Overall, the composition of the sample does not change substantially and, based on a number of criteria, the final sample appears to inherit the main properties of the survey data. Appendix Tables A.2 and A.3 provide information on the balance of the panel and additional descriptive statistics for the sample.

As discussed earlier, a basic prediction of the threshold-based policies used to describe irreversible investment decisions under uncertainty is that we should observe zero-investment episodes in capital expenditure data, corresponding to the region of inaction. However, the detection of such a pattern is often masked by aggregation of underlying data across capital expenditures on different types of assets, as well as across investment at different production locations.

This important feature of investment data has already been documented by Caballero, Engel, and Haltiwanger (1995) and Doms and Dunne (1998) for the United States; by Attanasio, Pacelli, and dos Reis (2003) for the United Kingdom; by Nilsen and Schiantarelli (2003) for Norway; by Bigsten and others (1999) and Pattillo (1998) for Africa; and by Gelos and Isgut (2001) for Latin America.

With reference to our data set, we provide some descriptive evidence that appears to confirm the above findings. In Table 1, we report the frequency of observations for which zero investment is reported, both in total and for different types of assets (buildings, plant and machinery, and transportation). The breakdown by

[3]See the Appendix for a more detailed description of the data set. Table A.1 provides a detailed breakdown of the sample according to the type of ownership, location, industry, and size of firms surveyed.

[4]Only 3.9 percent of the firms sampled in 1997 are listed.

[5]Again, the Appendix provides more details on this data set.

Table 1. Frequency of Zero-Investment and Zero-Disinvestment Episodes
(Breakdown by number of employees; in percent)

Employees	Buildings	Machinery	Transport	Total Investment	Total Disinvestment	Total Investment and Disinvestment
50–99	53.30	4.95	41.75	4.17	45.52	3.30
100–199	41.19	1.38	27.72	0.75	36.60	0.61
200–499	27.94	0.91	17.49	0.38	31.07	0.38
500–999	23.03	0.00	15.44	0.00	27.64	0.00
≥ 1,000	12.87	0.00	09.12	0.00	21.44	0.00

Note: Data refer to the period from 1991 to 1998 and cover 2,682 observations.

assets allows us to assess the importance of aggregation across different types of investment goods in concealing zero-investment episodes in the firm-level data. Because the breakdown is not available for earlier years, the data refer to all the firms in our sample from 1991 to 1998. We also report the frequency of observations for which zero disinvestment (that is, sales of capital goods) is reported, although here the breakdown by asset type is not available.

Taking employment as a proxy for firm size, it may be noticed that although years with zero total investment are rare, the frequency of zero-investment episodes tends to be higher for smaller firms. The frequency of zero-investment episodes is also higher when considering investment data disaggregated by type of asset. The frequency of zero-investment years for buildings and transportation approaches 50 percent for the smallest class of firms. Years with zero disinvestment are much more common than years with zero investment, although observations with zero disinvestment also become increasingly rare as we consider larger firms.

To illustrate the effect of aggregation across different production locations, we report in Table 2 the frequency of zero-investment and zero-disinvestment episodes broken down according to the number of plants operated by each firm. Although this table refers only to selected years, for which information on the number of plants operated by each firm is available, it appears to confirm the previous insight

Table 2. Frequency of Zero-Investment and Zero-Disinvestment Episodes
(Breakdown by number of plants; in percent)

Plants	Building	Machinery	Transport	Total Investment	Total Disinvestment	Total Investment and Disinvestment
1	38.96	2.19	23.75	1.46	35.57	1.20
2	26.49	1.32	17.55	1.32	32.58	1.12
3	26.35	0.00	13.51	0.00	31.36	0.00
≥ 4	16.67	0.00	07.41	0.00	23.53	0.00

Note: Data refer to the period from 1992 to 1995 only and cover 1,689 observations.

that the frequency of zero-investment episodes tends to be higher for smaller firms with fewer production units, for which aggregation over different assets and plants is likely to be less important. These preliminary findings suggest that the investment behavior of the firms in our sample may be consistent with the predictions of threshold-based policies.

IV. Measuring Uncertainty

There is no consensus in the empirical literature about the most appropriate measure of uncertainty. This is likely to be due to the fact that uncertainty is unobservable to the econometrician and therefore one has to resort to a proxy in empirical modeling. We can broadly divide those proxies into two categories, according to whether they are backward-looking or forward-looking proxies.

In the former case, researchers have used past data to compute the unconditional variance of a particular economic variable, such as sales growth, and have employed this as a proxy for uncertainty. Along similar lines, other researchers have attempted to measure uncertainty by estimating a statistical model of the underlying conditional variance of particular variables (see, for example, Huizinga, 1993; Episcopos, 1995; and Price, 1995 and 1996). However, the resulting autoregressive conditional heteroscedasticity-based or generalized autoregressive conditional heteroscedasticity-based measures of uncertainty would depend on the validity of these statistical models. Moreover, because investment is a forward-looking decision, backward-looking proxies may not capture well the degree of uncertainty at the moment when investment decisions are made.

Interestingly, Ferderer (1993) uses the implicit risk premium on long-term bonds embedded in the term structure of interest rates to proxy for aggregate uncertainty. This forward-looking proxy, however, captures only one source of uncertainty, namely that related to future interest rates, whereas much wider dimensions of uncertainty may be relevant for investment decisions. In addition, this measure of uncertainty is countercyclical and leads the business cycle. As a result, investment may be reacting to changes in the level of demand, rather than to the uncertainty surrounding that level.

Other researchers, such as Guiso and Parigi (1999), have employed—with reference to Italian company data—measures derived from managers' ex ante assessments of uncertainty about future outcomes for (potentially) relevant variables such as demand growth. The advantage of this approach is that the resulting measures of uncertainty are based on the perceptions of managers who are well informed about the firm's environment, and whose views are directly relevant to the investment decisions being studied. Such measures are rarely available, however, because they require extensive and costly surveys to be undertaken. Even the Guiso and Parigi measure is available only for a single cross-section and thus, if the perceived level of uncertainty varies over time, is unsuitable for the investigation of investment dynamics.

Leahy and Whited (1996) and Bloom, Bond, and Van Reenen (2003) opt for an alternative approach by deriving a proxy for firm-level uncertainty from share price data. By taking the annual variance of daily share returns, they derive a time-varying assessment by informed market participants of the uncertainty surrounding the economic environment in which the firm operates. Moreover, this measure has the advantage of being forward-looking and weighs all possible sources of uncertainty—not only demand uncertainty—affecting the future profitability of investment decisions. A disadvantage of this type of uncertainty measure is the possibility that share prices may deviate significantly from firms' fundamental values, so that volatility may reflect not only changes in fundamentals but also the influence of bubbles and noise traders. Moreover, this approach is only possible for firms whose shares are publicly quoted.

Our measure of uncertainty is based on the accuracy of firms' forecasts of their own investment spending one year ahead. The idea is that if a firm faces no uncertainty, it would know its future investment level, and these forecast errors would be zero. The more uncertain the environment in which the firm operates, the more likely it is that next period's investment will be different from the firm's current forecast. This will be reflected in a higher variance of the firm's forecast errors. We therefore construct a measure of the firm's uncertainty based on the ex post errors in the one-year-ahead investment forecasts of firms' managers, as reported in the SIM.[6] However, because the forecast errors for the level of investment are also likely to be related to firm size, we consider a measure of the forecast error normalized by the (known) level of the firm's existing capital stock.

In particular, let $E_{i,t-1}$ (I_{it}) be the forecast reported by firm i at time t–1 for its investment spending at time t. Dividing by the firm's capital stock at time t–1, we obtain $E_{i,t-1}$ $(I_{it}/K_{i,t-1})$ or the one-year-ahead expected investment rate. Then using the same firm's reported investment spending one period later (I_{it}), the ex post forecast error $(fe)_{it}$ is as follows:

$$(fe)_{it} = (I_{it}/K_{i\,t-1}) - E_{i\,t-1}(I_{it}/K_{i\,t-1}). \tag{5}$$

To ensure that positive as well as negative forecast errors are equally weighted, equation (5) can be squared to obtain the following:

$$\left[(fe)_{it}\right]^2 = \left[(I_{it}/K_{i,t-1}) - E_{i,t-1}(I_{it}/K_{i,t-1})\right]^2. \tag{6}$$

The variance of these forecast errors can be estimated for alternative sample periods. At one extreme, we could use the variance of the forecast errors computed using all the available observations for a particular firm:

$$\sigma_{it} = 1\!\!\big/_{T} \sum_{t=1}^{T} [(fe)_{it}]^2, \tag{7}$$

where T is the number of years that forecast errors for firm i are observed in the sample. However, using σ_{it} as the measure of uncertainty in our empirical investment

[6]One disadvantage of our measure is that the predictability of future investment may itself depend on the level of adjustment costs. An implicit assumption of our empirical specification, in common with most of the previous literature, is that all firms in the sample face similar levels of adjustment costs. Unpredictability of future investment will then reflect uncertainty in the firm's environment, rather than unusually low costs of adjustment.

equations would not allow us to investigate the long-run effects of changes in the level of uncertainty on the level of the capital stock while controlling for unobserved firm-specific effects, because there is no variation over time in this measure. The assumption that the uncertainty in each firm's environment is constant over time may also be unduly restrictive. At the other extreme, we could simply use $[(fe)_{it}]^2$ as a measure of uncertainty at time t. In this case, however, other concerns would arise owing to the fact that an estimate of the variance based on only a single observation would be very noisy.

To strike a balance between these conflicting concerns, our main results are reported using the following rolling measure of uncertainty:

$$\sigma_{it} = \frac{1}{t}\sum_{s=1}^{t}\left[(fe)_{it}\right]^2. \tag{8}$$

This measure does vary over time and therefore allows us to explore the long-run impact of uncertainty on capital accumulation. In addition, the forecast error variance is estimated using a minimum number of observations. In the empirical analysis, we use an estimated rolling variance of the forecast errors based on at least four observations. In terms of equation (8), this is equivalent to requiring $t \geq 4$. We obtained similar empirical results using alternative measures of the variance of these forecast errors, based on shorter or longer minimum observation periods.

Unlike some previous measures used in the empirical literature, σ_{it} in equation (8) is not related to any specific source of uncertainty and should reflect uncertainty about a range of factors that may be relevant for capital expenditure decisions. For example, firms face uncertainty related to wages, prices, costs of raw materials, exchange rates, technology, consumer tastes, and government policies. Importantly, in contrast with much previous research,[7] our proxy is based on the assessment of decision makers who are informed about and have direct responsibility for the planning and implementation of a firm's investment projects. In this respect, our measure is similar to that employed by Guiso and Parigi (1999). However, their measure was based on a single cross-section and was time-invariant.

Before turning to the econometric analysis, in Tables 3 and 4 we present some descriptive statistics on the uncertainty measure and how it relates to some observable features in our sample, such as firm size and the industrial sector in which a firm operates. As Table 3 shows, at least on average, the realized investment rates are reasonably close to firms' ex ante expectations. This is also true for subsamples of firms defined by whether our measure of uncertainty is relatively high or relatively low. Firms facing lower uncertainty tend to have higher investment rates than firms facing higher uncertainty, and this is reflected in their ex ante expectations. Table 3 also confirms that firms in the subsample with lower forecast error variance also have, on average, smaller forecast errors in absolute value.

[7]See Carruth, Dickerson, and Henley (2000) for a survey of the most common measures of uncertainty employed in the investment literature.

Table 3. Investment and Expected Investment Rates

Variable		Low Uncertainty	High Uncertainty	Total Sample
$\left(\frac{I_{it}}{K_{i,t-1}}\right)$	Mean	0.1174	0.0749	0.0962
	Median	0.0982	0.0613	0.0767
$E_{i,t-1}\left(\frac{I_{it}}{K_{i,t-1}}\right)$	Mean	0.1169	0.0706	0.0937
	Median	0.0942	0.0598	0.0766
$abs\ [(fe)_{it}]$	Mean	0.0103	0.0719	0.0411
	Median	0.0095	0.0505	0.0243

Note: Low Uncertainty (High Uncertainty) refers to the subsample with measured uncertainty maller (greater) than the sample median.

Table 4 reports that firms facing relatively high uncertainty, according to our measure, are more likely to be found in the sectors producing electrical goods, transport, machinery, leather and footwear, and other manufacturing goods. The smallest firms in our sample—that is, those employing between 50 and 99 employees—are more likely to be in the high-uncertainty group. There is no clear relation, however, to firm size among firms with 100 or more employees.

Table 4. Firms with Low and High Uncertainty

Industrial Sector	Low Uncertainty	High Uncertainty
Metallurgy	53.42	46.58
Nonmetallic mineral products	58.59	41.41
Chemical products	48.66	51.34
Machinery	46.32	53.68
Electrical goods	42.86	57.14
Trains, ships, planes, and motor vehicles	45.24	54.76
Food products, beverages, and tobacco	54.72	45.28
Clothing and textiles	50.68	49.32
Leather and footwear	45.40	54.60
Timber and furniture	47.83	52.17
Paper, printing, and publishing	52.17	47.83
Rubber and plastic goods	50.30	49.70
Other manufacturing goods	42.58	57.42
Size		
50–99 employees	46.21	53.79
100 or more employees	50.00	50.00

Note: Low Uncertainty (High Uncertainty) refers to the frequency of the observations for which our measure of uncertainty is smaller (greater) than the overall sample median.

Overall, this indicates that idiosyncratic firm-level variation in uncertainty is potentially important, because variation in uncertainty is not well explained by sector or firm size.[8] Firms with a higher level of measured uncertainty are found to invest less than those with a lower level of measured uncertainty. This suggests that our measure of uncertainty contains some information that is relevant for understanding investment. The nature of this relationship is explored more thoroughly in the next section.

V. Econometric Analysis

Estimation

The empirical specification given by equation (4) requires the estimation of a dynamic panel data model. Arellano and Bond (1991) have developed a generalized method of moments (GMM) estimator to account for the presence of lagged dependent variables, the endogeneity of current-dated explanatory variables, and unobserved firm-specific effects. Their first-differenced GMM estimator relies on equations in first-differences from which firm-specific effects are eliminated; regressors can then be instrumented using lagged endogenous variables provided that the time-varying component of the model's residuals exhibits limited serial correlation. Arellano and Bond (1991) also provide useful tests for inspecting the degree of serial correlation in the residuals.

According to Blundell and Bond (1998), in dynamic panel data models in which the individual series are reasonably persistent and in which the number of time-series observations is relatively small, lagged levels of the series provide only weak instruments for variables in first-differences and the resulting first-differenced GMM estimates exhibit large finite sample biases. Their extended GMM estimator makes use of lagged differences of endogenous variables as instruments for equations in levels, in addition to lagged levels of endogenous variables as instruments for equations in first-differences (see also Arellano and Bover, 1995). Monte Carlo simulations have shown that this extended GMM estimator yields substantial gains in the precision of parameter estimates and potentially dramatic reductions in the finite sample bias, provided that these additional instruments are valid. This assumption can be tested using standard tests of overidentifying restrictions.

Monte Carlo simulations also have shown that the usual asymptotic standard errors of the efficient two-step version of this GMM estimator are affected by a serious finite sample bias that can result in a misleading inference. Windmeijer (2005) analyzes this problem and proposes a finite sample correction. Importantly, we apply this correction to the variance of the two-step GMM estimator, so that the two-step estimates can be used to gauge the robustness of the results provided by the one-step GMM estimator.

[8]Guiso and Parigi (1999) also reported that there was no clear relationship between their firm-level measure of uncertainty and a set of observable firm characteristics. The only exception was whether firms were privately owned or state-owned. In our sample, the latter group is not present.

Empirical Results and Their Policy Implications

Our preferred results treat current sales as predetermined, with the precise set of instruments reported in detail in the note to the tables. The validity of these instruments is assessed by means of a Sargan test of overidentifying restrictions. Our main results are robust to differences in this precise choice of the instruments. Similarly, although we report the results based on this extended GMM estimator, our main findings were also obtained using alternative estimators such as within groups, ordinary least squares, and first-differenced GMM.

The one-step and two-step GMM results with heteroscedasticity-robust standard errors are reported in Tables 5 and 6, respectively. The results have been computed using Dynamic Panel Data 98 (DPD98) for Gauss, with a modification provided by Windmeijer (2005) to compute the corrected variance matrix for the two-step estimator.

Before commenting on these results, we note that cash flow was not found to be statistically significant in any of the empirical specifications we considered, nor

Table 5. Investment Equations

(One-step GMM results)

$(I_{it}/K_{i,t-1})$	(1)	(2)	(3)	(4)	(5)
Δy_{it}	0.1163	0.1028	0.2469	0.2475	0.1142
	(0.0304)	(0.0316)	(0.0588)	(0.0589)	(0.0171)
$\Delta y_{i,t-1}$	0.1456	0.1402	0.1364	0.1359	0.1394
	(0.0239)	(0.0237)	(0.0175)	(0.0175)	(0.0177)
$(k–y)_{i,t-2}$	–0.1354	–0.1335	–0.1356	–0.1351	–0.1383
	(0.0273)	(0.0271)	(0.0203)	(0.0205)	(0.0205)
$(\Delta y_{it})^2$	—	0.3376	0.3282	0.3296	0.2875
		(0.1281)	(0.1215)	(0.1222)	(0.1189)
$\sigma_{it}\ \Delta y_{it}$	—	—	–0.9209	–0.9279	—
			(0.3862)	(0.3870)	
$\sigma_{i,t-1}$	—	—	—	0.0199	0.0025
				(0.0545)	(0.0544)
Sargan (p)[1]	0.34	0.37	0.46	0.44	0.34
LM2 (p)[2]	0.71	0.83	0.77	0.76	0.86
Observations	4,192	4,192	4,192	4,192	4,192
Firms	564	564	564	564	564

Note: GMM = generalized method of moments. Asymptotically robust standard errors are reported in parentheses below the coefficients; estimation by GMM-SYSTEM using Dynamic Panel Data 98 (DPD98) package one-step results; full set of time dummies included, results available upon request; — = variable not included. In column (1), instruments are $(I_{i,t-2}/K_{i,t-3})$, $(I_{i,t-3}/K_{i,t-4})$, $y_{i,t-1}$, $y_{i,t-2}$, $y_{i,t-3}$, $(k–y)_{i,t-2}$, and $(k–y)_{i,t-3}$ in the differenced equations; $\Delta(I_{i,t-1}/K_{i,t-2})$ and Δy_{it} in the level equations. In column (2), we also include $(\Delta y_{i,t-1})^2$, $(\Delta y_{i,t-2})^2$, and $(\Delta y_{i,t-3})^2$ in the set of instruments for the differenced equations. In columns (3) to (5), we further include $\sigma_{i,t-2}$, $\sigma_{i,t-3}$, and $\sigma_{i,t-4}$.

[1]Sargan is a Sargan-Hansen test of overidentifying restrictions (p-value reported).

[2]LM2 is the Arellano-Bond test for the absence of second-order serial correlation in the first-differenced residuals (p-value reported).

Table 6. Investment Equations
(Two-step GMM results)

$(I_{it}/K_{i,t-1})$	(1)	(2)	(3)	(4)	(5)
Δy_{it}	0.1030	0.0992	0.2187	0.2197	0.0992
	(0.0255)	(0.0265)	(0.0534)	(0.0531)	(0.0164)
$\Delta y_{i,t-1}$	0.1228	0.1210	0.1160	0.1157	0.1161
	(0.0219)	(0.0218)	(0.0168)	(0.0169)	(0.0166)
$(k-y)_{i,t-2}$	–0.1314	–0.1277	–0.1158	–0.1155	–0.1194
	(0.0288)	(0.0235)	(0.0178)	(0.0179)	(0.0178)
$(\Delta y_{it})^2$	—	0.2258	0.2295	0.2316	0.1923
		(0.1021)	(0.0969)	(0.0977)	(0.0965)
$\sigma_{it}\ \Delta y_{it}$	—	—	–0.8247	–0.8331	—
			(0.3439)	(0.3472)	
$\sigma_{i,t-1}$	—	—	—	0.0115	0.0054
				(0.0477)	(0.0479)
Sargan (p)[1]	0.34	0.37	0.46	0.44	0.34
LM2 (p)[2]	0.74	0.78	0.64	0.64	0.71
Observations	4,192	4,192	4,192	4,192	4,192
Firms	564	564	564	564	564

Notes: Asymptotically robust standard errors are reported in parentheses below the coefficients; estimation by GMM-SYSTEM using DPD98 package two-step results, as modified by Windmeijer (2005); full set of time dummies included, results available upon request; — = variable not included. In column (1), instruments are $(I_{i,t-2}/K_{i,t-3})$, $(I_{i,t-3}/K_{i,t-4})$, $y_{i,t-1}$, $y_{i,t-2}$, $y_{i,t-3}$, $(k-y)_{i,t-2}$, and $(k-y)_{i,t-3}$ in the differenced equations; $\Delta(I_{i,t-1}/K_{i,t-2})$ and Δy_{it} in the level equations. In column (2), we also include $(\Delta y_{i,t-1})^2$, $(\Delta y_{i,t-2})^2$, and $(\Delta y_{i,t-3})^2$ in the set of instruments for the differenced equations. In columns (3) to (5), we further include $\sigma_{i,t-2}$, $\sigma_{i,t-3}$, and $\sigma_{i,t-4}$.

[1]Sargan is a Sargan-Hansen test of overidentifying restrictions (p-value reported).

[2]LM2 is the Arellano-Bond test for the absence of second-order serial correlation in the first-differenced residuals (p-value reported).

was it informative as an instrument. This result, pointing to a lack of liquidity effects for the firms sampled, is consistent with previous evidence on Italian company data (see, among others, Bettoni, 2000; and Carpenter and Rondi, 2000). Furthermore, the hypothesis of a long-run elasticity of capital with respect to output of unity was not rejected by the data at conventional significance levels and is imposed throughout. Overall, the diagnostic test results are satisfactory, with no evidence of second-order serial correlation in the first-differenced residuals, and the Sargan test does not reject the validity of the overidentifying restrictions.

In reporting our results, we start from the simplest linear specification of the error-correction mechanism model and then present various extensions. Overall, the results using the one- and two-step GMM estimators are similar, as can be seen by comparing Tables 5 and 6. Column (1) in Tables 5 and 6 reports estimates for the most basic specification that does not account for nonlinear effects of real sales growth $(\Delta y_{it})^2$ nor for the interaction term between real sales growth and uncertainty $(\sigma_{it}\ \Delta y_{it})$. The point estimates of the coefficients on current and lagged growth in real sales are similar to results reported in previous studies (see, for example, Bond, Harhoff, and Van Reenen, 1999). The coefficient on the error-correction term, negatively signed and statistically significant, is consistent with error-correcting behavior.

In column (2) of Tables 5 and 6, the inclusion of the squared sales growth rate term allows us to test the null hypothesis of a linear accelerator effect against the alternative of nonlinear dynamics predicted by the real options model. The coefficient on this quadratic term is large, positive, and significantly different from zero at conventional levels, indicating a convex response of investment to demand shocks.

In column (3) of Tables 5 and 6, the inclusion of the uncertainty interaction term allows us to test the null hypothesis of a common response of investment to demand shocks against the alternative of a heterogeneous response for firms that face different levels of measured uncertainty. Again, our results clearly reject this null hypothesis. Uncertainty exerts a powerful impact on firms' short-run investment behavior, with a weaker response to demand shocks at higher levels of uncertainty, which is exactly the effect predicted by the partial irreversibility model. The coefficient on this interaction term is large, negative, and significantly different from zero.

Column (4) of Tables 5 and 6 allows for a further effect of uncertainty on the long-run level of the capital stock. Although the relevance of the short-run effect on investment dynamics, as proxied by the interaction term, is confirmed, the long-run effect of uncertainty is found to be both small and statistically insignificant. Finally, in column (5) of Tables 5 and 6, we reestimate the investment equation allowing only for the long-run effect of uncertainty, but again we do not identify any significant long-run effect.

In Appendix Tables A.4 and A.5, we report results for two additional specifications that explore whether the impact effect of demand shocks on investment varies with firm size rather than with the level of uncertainty.[9] Here we include an additional interaction term ($k_{i,t-1}\ \Delta y_{it}$) using the capital stock at the end of the previous period ($k_{i,t-1}$) as a measure of firm size. The coefficients on this additional interaction term are insignificantly different from zero, whereas those on the interaction between real sales growth and measured uncertainty continue to be negative and significant. This confirms that the significant heterogeneity found in the impact effect of demand shocks for firms facing different levels of uncertainty is not simply an artifact of imposing common coefficients for smaller and larger firms.

Overall, these findings are consistent with those reported by Bloom, Bond, and Van Reenen (2003) for a sample of U.K. manufacturing firms, using share price volatility as a measure of uncertainty. The theory of investment under partial irreversibility predicts that firms' short-run investment decisions become less responsive to demand shocks at higher levels of uncertainty because a more cautious policy has a higher payoff. This theoretical prediction is supported by our empirical findings. The policy implications of this result are potentially important: investment

[9]We thank an anonymous referee for this suggestion.

reacts more sluggishly to policy interventions when firms operate in a more uncertain environment. The level of uncertainty is therefore important in predicting the short-run effects of policy interventions. This result on the effect of uncertainty on investment dynamics may also shed light on why empirical estimates of mainstream investment equations often fail to perform satisfactorily: the omission of interactions between uncertainty and output growth, and nonlinear terms in output growth, in standard empirical models may account for unstable parameter estimates across different sample periods.

VI. Conclusion

In this paper, we have tested the predictions of a model of investment under partial irreversibility using data on Italian firms. Following Bloom, Bond, and Van Reenen (2003), we emphasize that these models predict a weaker response of investment to demand shocks at higher levels of uncertainty, as well as a strictly convex response of investment to current demand shocks. We use data on firms' expectations of their own future investment, available in the Bank of Italy's SIM, to construct a measure of uncertainty based on the variance of these firms' forecast errors. We find the predicted weaker response of investment to real sales growth for firms that face a higher level of uncertainty, and we also find the predicted nonlinear response of investment to real sales growth.

These findings have potentially important implications for the effects of monetary and fiscal policies on firms' investment spending, suggesting that a given demand stimulus will tend to have weaker effects in the short run at higher levels of uncertainty. Our results suggest that allowing for these heterogeneous and nonlinear dynamics may be important in developing stable econometric models of investment for more aggregated data. Finally, the effect of uncertainty on capital accumulation in the long run, which is theoretically ambiguous in this class of models, is not clearly identified from our empirical analysis. Whether this reflects the limited time-series variation in our measure of uncertainty, or whether it is a deeper feature of investment behavior, remains an important question for future research.

APPENDIX

The data set used in this paper has resulted from the merging of two sources: the Bank of Italy Survey of Investment in Manufacturing (SIM) and the Company Accounts Data Service (CADS).

Survey of Investment in Manufacturing

The Bank of Italy carries out an annual survey of realized and planned investments in fixed capital among a randomly selected sample of about 1,000 firms representative of the manufacturing industry. The basic version of the survey was first conducted in the 1970s, and results have been available in electronic format since the 1984 edition. The relevant population refers to businesses operating in the manufacturing industry that have more than 50 employees, with the exclusion of the energy sector, which has been surveyed only since 1999. The unit surveyed is the firm and the sample is stratified on the basis of firm size, geographic location, and sector of activity, according to the joint frequency distribution compiled by the Italian National Statistics

Institute (ISTAT). Although the number of employees is taken as the measure of firm size, the sector of activity refers to the ISTAT three-digit ATECO-91 classification, which is consistent with the NACE-CLIO (General Industrial Classification of Economic Activities in the European Communities, *Nomenclature générale des Activités économiques dans les Communautés Européennes*) international standards. The geographic location is taken to be the region in which the firm has established its legal headquarters.

Despite its name, the survey collects data on a number of variables besides investment: in addition to indicating the reasons for not fully realizing their investment plans, firms are asked about employment figures and their expected growth, the number of effective hours worked, their total and export turnover, and the change in the price of the goods they produce. In recent years, firms have also been surveyed about their expected turnover, the expected change in their product prices, and their ownership structure, and they have been asked to report whether they are listed on a stock market or belong to a holding. For selected years, data on the number of plants operated by each firm are also available. Starting from 1992, an additional section has been added to the survey. Firms have been surveyed about e-commerce (1999), labor firing costs (1998), capital stock and foreign investments (1997), pricing policies and market structure (1996), technological change (1995), wage bargaining (1994), product demand expectations (1993), and ownership structure (1992).

The survey is carried out through interviews by highly trained Bank of Italy officials who usually have established long-term relationships with firms' managers. Questionnaires are sent out by the end of December of the survey year and are collected by April of the following year at the latest. Responses are carefully scrutinized by specialized teams within the Bank. These teams also check with the firms on any possible inconsistencies arising from their responses. In the survey, firms are asked whether a major corporate event has occurred in the year (a merger or an acquisition, and so on) and to report data on a basis consistent with the previous year.

The main results from the survey are published each year in the Bank of Italy's annual report. So far, the resulting data set has fed into several studies on the structure and the behavior of the Italian manufacturing sector.[10]

Company Accounts Data Service

The CADS is provided by Centrale dei Bilanci, an institution owned by the Bank of Italy and a consortium of commercial banks. The data set comprises roughly 800 items from income statements, balance sheets, and other nonaccounting sources for about 40,000 financial and nonfinancial firms. The data are standardized to ensure comparability across firms and are available on an annual basis since 1981. The sample is not randomly drawn because a firm enters the data set after applying for a loan from one of the banks owning Centrale dei Bilanci.

Estimation of Capital Stocks

Capital stocks have been estimated through a perpetual inventory method:

$$P_t^I K_t = (1-\delta)P_{t-1}^I K_{t-1}(P_t^I/P_{t-1}^I) + P_t^I I_t - P_t^I DISP_t \tag{A1}$$

[10]See, among others, Guiso and Parigi (1999) and Nucci and Pozzolo (2001). See Barca and others (1996) for a more detailed description of the methodology and the main features of the SIM.

where:

K_t = end-of-period real capital stock,
P_t^I = price of investment goods,
I_t = real gross investment,
$DISP_t$ = real revenues from sales of investment goods, and
δ = depreciation rate.

We have assumed that capital depreciates at an annual rate of 8 percent and that the benchmark capital stock is, on average, three years old. The two-digit price indices of investment goods are from ISTAT.

Cash Flow

Cash flow, equal to net profits plus depreciation, is obtained from Centrale dei Bilanci.

Disposals

Revenues from sales of investment goods are from Centrale dei Bilanci.

Investment

Gross total investment in fixed assets is from the SIM. Sampled firms are asked to report—for the survey year—the total of fixed investments in Italy and their breakdown into buildings, plant and machinery, and transportation investments. For data quality control, firms are also asked to report data (under the same headings) for the previous year.

Output

Sales deflated by two-digit producer price indices have been used as the proxy for real output.

Table A.1. Comparison of SIM and SIM-CADS Samples

	SIM-CADS		SIM	
	Observations	Percent	Observations	Percent
Sector				
Private	4,192	100	13,988	94.05
State-owned	0	0	885	5.95
Location				
North	3,175	75.74	10,405	69.96
Center	695	16.58	2,563	17.23
South	322	7.68	1,905	12.81
Industrial Sector				
Metallurgy	438	10.45	1,664	11.19
Nonmetallic mineral products	396	9.45	1,176	7.91
Chemical products	409	9.76	1,274	8.57
Machinery	598	14.27	2,254	15.15
Electrical goods	259	6.18	1,313	8.83
Trains, ships, planes, and motor vehicles	210	5.01	1,002	6.74

Table A.1 *(concluded)*

	SIM-CADS		SIM	
	Observations	Percent	Observations	Percent
Food products, beverages, and tobacco	359	8.56	1,416	9.52
Clothing and textiles	739	17.63	2,238	15.05
Leather and footwear	163	3.89	599	4.03
Timber and furniture	69	1.65	234	1.57
Paper, printing, and publishing	230	5.49	680	4.57
Rubber and plastic goods	167	3.98	602	4.05
Other manufacturing goods	155	3.70	421	2.83
Size				
50–99 employees	579	13.81	2,925	19.67
100–199 employees	994	23.71	3,246	21.82
200–499 employees	1,247	29.75	4,203	28.26
500–999 employees	669	15.96	2,219	14.92
1,000 and more employees	703	16.77	2,280	15.33
Firm size (employees median)	285		266	
Listed firms[1]	85	5.06	181	3.89
Firms belonging to a holding[2]	668	67.34	1,922	62.95
Total observations	4,192		14,873	

[1]Reference year: 1997.
[2]Reference years: from 1996 to 1998.

Table A.2. Balance of Panel

Start	End	1990	1991	1992	1993	1994	1995	1996	1997	1998	Firms
1987		16	18	20	20	18	14	7	16	85	214
1988		—	8	4	6	2	1	1	2	16	40
1989		—	—	1	3	1	4	1	1	8	19
1990		1	—	—	17	18	8	7	12	73	136
1991		—	—	—	—	3	2	6	7	16	34
1992		—	—	—	—	—	4	3	6	13	26
1993		—	—	—	—	—	—	13	5	31	49
1994		—	—	—	—	—	—	—	7	20	27
1995		—	—	—	—	—	—	—	—	19	19
1996		—	—	—	—	—	—	—	—	—	—
1997		—	—	—	—	—	—	—	—	—	—
1998		—	—	—	—	—	—	—	—	—	—
Firms		17	26	25	46	42	33	38	56	281	564

Table A.3. Further Descriptive Statistics

Variable	Median	Mean	Standard Deviation
Real sales growth	0.0253	0.0204	0.1377
Employment	285	877	4,091
Observations per firm	9	8.5	2.7

Table A.4. Further Investment Equations
(One-step GMM results)

$(I_{it}/K_{i,t-1})$	(1)	(2)
Δy_{it}	0.4836	0.4865
	(0.2922)	(0.2932)
$\Delta y_{i,t-1}$	0.1357	0.1351
	(0.0173)	(0.0174)
$(k-y)_{i,t-2}$	–0.1341	–0.1335
	(0.0200)	(0.0204)
$(\Delta y_{it})^2$	0.3363	0.3379
	(0.1254)	(0.1262)
$\sigma_{it}\ \Delta y_{it}$	–1.0066	–1.0149
	(0.4009)	(0.4027)
$\sigma_{i,t-1}$	—	0.0213
		(0.0547)
$k_{i,t-1}\ \Delta y_{it}$	–0.0231	–0.0233
	(0.0277)	(0.0277)
Sargan (p)[1]	0.43	0.40
LM2 (p)[2]	0.73	0.72

Notes: GMM = generalized method of moments. Asymptotically robust standard errors are reported in parentheses below the coefficients; estimation by GMM-SYSTEM using Dynamic Panel Data 98 (DPD98) package one-step results; full set of time dummies included, results available upon request; — = variable not included; instruments are the same as those reported in the notes to Tables 5 and 6.

[1]Sargan is a Sargan-Hansen test of overidentifying restrictions (p-value reported).

[2]LM2 is the Arellano-Bond test for the absence of second-order serial correlation in the first-differenced residuals (p-value reported).

Table A.5. Further Investment Equations
(Two-step results)

$(I_{it}/K_{i,t-1})$	(1)	(2)
Δy_{it}	0.4419	0.4446
	(0.2722)	(0.2733)
$\Delta y_{i,t-1}$	0.1159	0.1156
	(0.0168)	(0.0168)
$(k-y)_{i,t-2}$	–0.1141	–0.1136
	(0.0179)	(0.0181)
$(\Delta y_{it})^2$	0.2406	0.2430
	(0.1012)	(0.1022)
$\sigma_{it}\ \Delta y_{it}$	–0.9296	–0.9397
	(0.3745)	(0.3788)
$\sigma_{i,t-1}$	—	0.0128
		(0.0482)
$k_{i,t-1}\ \Delta y_{it}$	–0.0214	–0.0215
	(0.0251)	(0.0252)
Sargan (p)[1]	0.43	0.40
LM2 (p)[2]	0.73	0.72

Notes: Asymptotically robust standard errors are reported in parentheses below the coefficients; estimation by GMM-SYSTEM using DPD98 package two-step results as modified by Windmeijer (2005); full set of time-dummies included, results available upon request; — = variable not included; instruments are the same as those reported in the notes to Tables 5 and 6.

[1]Sargan is a Sargan-Hansen test of overidentifying restrictions (p-value reported).

[2]LM2 is the Arellano-Bond test for the absence of 2nd-order serial correlation in the first-differenced residuals (p-value reported).

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