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ABSTRACT

Idiosyncratic and Common Shocks to Investment Decisions*

This Paper shows how microeconomic data on investment plans can be used to study the structure of risk faced by firms. Revisions of investment plans form a martingale, and thus reveal the underlying shocks driving investment. We decompose revisions in investment plans into micro, sector and aggregate shocks, and exploit stock market data to distinguish between structural (value-related) shocks and measurement error in investment revisions. Using panel data for US firms, we find that microshocks are not the dominant source of risk in investment decisions, and that much of the observed microvariation is actually due to heterogeneity in firm-level responses to aggregate shocks. Firms are able to diversify most idiosyncratic investment risk, and they do not appear to be liquidity constrained.

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Keywords: aggregate shocks, heterogeneity, investment and microshocks

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NON-TECHNICAL SUMMARY

It is a well documented fact that there is large variation in investment rates across plants and firms. This heterogeneity has been widely interpreted as showing that micro-level factors are the main determinant of investment decisions. Investment, however, adjusts slowly to changes in economic factors, including input prices, demand and technological innovation. Observed changes in investment in any year will reflect a distributed lag of the accumulated information, or 'shocks', that affect calculations of investment profitability. Each of these factors is likely to have both a firm-specific (idiosyncratic) element and a component that is common across firms, at the sector or aggregate level. Moreover, the common factors may have idiosyncratic effects because firms react to them in different ways. For example, the impact of the interest rate on costs will depend on the capital structure of firms. For these reasons, the fact that most of the variation in observed investment rates is microvariation does not establish that the underlying shocks driving investment behaviour are primarily micro in origin. For this purpose, we need a way to identify those shocks.

Knowing whether investment is driven mostly by micro- or common shocks can tell us something about the effectiveness of capital and insurance markets. If capital markets work well, firms should be able to diversify the idiosyncratic risk they face. In that case, we should observe that investment decisions are primarily determined by common shocks, though possibly with firm-specific effects. Evidence that microshocks play an important role would suggest that firms are unable to diversify the microrisk effectively. Interestingly, it is common for researchers to interpret the substantial microvariation in observed investment rates as indicating that firms adjust to new private information in ways that are likely to promote efficient resource allocation. An empirical finding that microshocks are dominant would make this conclusion suspect. On the other hand, if common shocks dominate, and firms react to them in different ways, then these shocks also induce resource reallocation at the micro level. While the dominance of common shocks would suggest effective capital markets, the efficiency properties of this reallocation would depend on what factors are responsible for the heterogeneity in micro responses.

This Paper shows how microeconomic data on investment plans can be used to study the structure of risk faced by firms. The methodology is based on a simple idea: if firms use an investment decision rule that fully exploits all available information, then revisions of investment plans are a martingale and can be used to study the structure of the underlying shocks driving investment decisions. The Paper applies this idea to panel data on investment plans for 318 firms in the United States during the period 1950-73. We augment these investment plan data with information on the stock market rate of return for the firms, which provides an additional indicator (contaminated by measurement error) of the shocks driving investment. We use a latent variable model to decompose the variance in the revision of investment plans into a structural component (i.e. the part related to the firm's market value) and measurement error. We conduct this analysis at the micro, sector and aggregate levels. We also show how to estimate the degree of heterogeneity in the firm-level responses to aggregate shocks. Despite their age, the data illustrate the usefulness of information on investment plans when applied in this new way.

The empirical results show that idiosyncratic shocks do not account for much of the variation in investment decisions – no more than 25% of the structural variance in investment revisions. Moreover, nearly 75% of this microvariance is actually due to heterogeneity in micro level responses to aggregate shocks. This finding suggests that either microshocks are not prevalent or firms are able to diversify most of the idiosyncratic risk they face, but at the same time large variation in firm-specific responses to aggregate shocks creates the appearance of microrisk. We also conduct tests for whether the firms in our sample were liquidity-constrained in their investment decisions, but we do not find any supportive evidence. Taken together, the empirical findings in this Paper suggest that the capital markets worked fairly well for the medium to large firms in our sample period.

1 Introduction

It is a well-documented fact that there is substantial variation in investment rates across plants and firms (for a review, see Caballero 1998). This heterogeneity has been widely interpreted as showing that micro-level factors are the main determinant of investment decisions. However, investment adjusts slowly to changes in economic factors, including input prices, demand and technological innovation. Observed changes in investment in any year will reflect a distributed lag of the accumulated information, or "shocks," that affect calculations of investment profitability. Each of these factors is likely to have both a firm-specific (idiosyncratic) element and a component that is common across firms, at the sector or aggregate level. Moreover, the common factors may have idiosyncratic *effects* because firms react to them in different ways. For example, the impact of the interest rate on costs will depend on the capital structure of firms. For these reasons, the fact that most of the variation in observed investment rates is micro variation does not establish that the underlying shocks driving investment behaviour are primarily micro in origin. For this purpose, we need a way to identify those shocks.

Knowing whether investment is driven mostly by micro or common shocks can tell us something about the effectiveness of capital and insurance markets. If capital markets work well, firms should be able to diversify the idiosyncratic risk they face. In that case, we should observe that investment decisions are primarily be determined by common shocks, though possibly with firm-specific effects. Evidence that micro shocks play an important role would suggest that firms are unable to diversify the micro risk effectively. Interestingly, it is common for researchers to interpret the substantial micro variation in *observed investment rates* as indicating that firms adjust to new private information in ways that are likely to promote efficient resource allocation. An empirical finding that *micro shocks* are dominant would make this conclusion suspect. On the other hand, if common shocks dominate, and firms react to them in different ways, then these shocks also induce resource reallocation at the *micro* level. While the dominance of common shocks would suggest effective capital markets, the efficiency properties of this reallocation would depend on what factors are responsible for the heterogeneity in micro responses.

This paper proposes a new and simple method that exploits information on *investment plan*s to identify the relative importance of idiosyncratic and common shocks to capital investment decisions at the firm level. We find that idiosyncratic shocks do *not* account for much of the variation in investment decisions. This means either that micro shocks are not prevalent or that firms are able to diversify most of the idiosyncratic risk they face. We also find that firms respond in different ways to aggregate shocks. This heterogeneity induces idiosyncratic variation in investment decisions and thus exaggerates the appearance of micro risk. We conduct tests for whether the firms in our sample were liquidity-constrained in their investment decisions, but we do not find any supportive evidence. Taken together, the empirical findings in this paper suggest that the capital markets worked fairly well for the medium to large firms in our sample period.

The methodology we develop is based on a simple idea: revisions of investment plans are a martingale and thus can be used to study the structure of the underlying shocks driving investment decisions. The paper applies this idea to panel data on investment plans for U.S. firms. We augment these investment plan data with information on the firms' stock market rates of return, which provide an additional indicator (with measurement error) of the shocks driving investment. We use a factor model to decompose the variance in the revision of investment plans into a structural component (i.e., the part related to the firm's market value) and measurement error. We conduct this analysis at the micro, sector and aggregate levels. We also estimate the degree of heterogeneity in the firm-level responses to aggregate shocks.

The martingale property of investment revisions is similar, but not identical, to the seminal result in Hall (1978) that optimal consumption behaviour under rational expectations and perfect capital markets implies that the marginal utility of consumption should be a martingale. If marginal utility is linear, changes in the level of consumption represent news in permanent income or the interest rate. Liquidity constraints and other forms of imperfect capital markets have been used to explain the observed cross-sectional and time-series properties of consumption changes, which often violate the martingale property (Hall and Mishkin, 1982; Zeldes, 1989; Altug and Miller, 1990; Hayashi, Altonji and Kotlikoff, 1996). The martingale property for investment revisions is a more general property in that it does not require assumptions about the form of the optimal decision function or perfect capital markets. But this comes at a cost – it requires that we have information on *investment plans* of the firm, not just the actual investment expenditure.

The analysis is based on panel data on investment plans and financial information at the firm level. We constructed these data from annual surveys of actual investment and investment plans, originally gathered by the McGraw-Hill Publishing Company, and matched these data to Compustat information on the sample firms. The panel covers 318 firms in the United States during the period 1950-73 (the survey was discontinued). Despite their age, the data illustrate the usefulness of information on investment plans when applied in this way.

Most studies in the literature indicate that micro or sector level risk is more important than aggregate risk. These include studies on monthly output at the sectoral level (Long and Plosser, 1987), and plant-level heterogeneity in labor turnover (Lilien, 1982; Abraham and Katz, 1986; Davis and Haltiwanger, 1990; Davis, Haltiwanger and Shuh, 1997), productivity growth (Baily, Bartelsman and Haltiwanger, 1994), and investment in plant and equipment (Doms and Dunne, 1993; Caballero, Engel and Haltiwanger, 1995; Caballero, 1998). These studies primarily focus on the sources of risk at the *plant-level*, whereas this paper focuses on *medium to large firms*. Not surprisingly, we find that idiosyncratic shocks are less important at the firm level.

Perhaps more important is the difference in methodology we adopt. Previous research is based on the decomposition of changes in the observed levels of economic variables, including job reallocation, investment and productivity growth. Unless these variables are random walks, this is not equivalent to studying the underlying shocks driving the decisions. Analysing the observed changes can either understate or overstate the role of genuine micro shocks. Since covariation among agents can arise from the transmission of micro shocks through various mechanisms (Long and Plosser, 1983; Cooper and Haltiwanger, 1991; Jovanovic, 1987), micro shocks may be misinterpreted as aggregate shocks. On the other side, there may be heterogeneity in the way in which agents respond to aggregate shocks, which will cause us to overestimate the importance of idiosyncratic risk. To address these concerns, we study the revisions in investment plans rather than changes in levels of actual investment. Since revisions are a martingale (confirmed in Section 4), they contain direct information on the shocks. Combining this information with data on the stock market rate of return, we are able to distinguish between "fundamental" shocks in investment revisions (reflected in stock market value) and measurement error. We also provide a way to estimate the degree of heterogeneity in micro-level responses to aggregate shocks, which allows us to quantify the effects of micro shocks and heterogeneity.

The empirical results show that micro shocks account for no more than 25 percent of the structural variance in investment revisions. Moreover, it turns out that nearly 75 percent of this micro variance is due to heterogeneity in firms' responses to aggregate shocks. This finding suggests that firms in this sample were quite successful at diversifying idiosyncratic risk, but large variation in firm-specific responses to aggregate shocks creates the appearance of micro risk. If this finding is confirmed by studies using other sample periods and countries, it may indicate that dynamic structural models that incorporate idiosyncratic risk but not aggregate risk are too restrictive (e.g., Ericson and Pakes, 1993). We also find that investment revisions are related to the news in sales, factor prices and cash flow, as expected, but there is no evidence that firms are liquidity-constrained. In short, the evidence supports the hypothesis that capital markets were largely effective for the medium to large firms in our sample.

The paper is organised as follows. Section 2 presents the analytical framework. Section 3 describes the data set, and Section 4 confirms that revisions in investment plans satisfy the martingale property. The factor model is developed in Section 5, and the empirical results are presented in Section 6, including the decomposition of investment revisions into micro, sector and aggregate shocks. Section 7 extends the model to allow for heterogeneity in the micro responses to aggregate shocks. Section

8 examines the empirical determinants of investment revisions, including "news" in sales, factor prices and cash flow at the firm level.

2 Analytical Framework

Consider a firm that produces output with capital and a set of variable inputs. All inputs are chosen to maximise the expected present value of net cash flow, conditional on the information set available to the firm in period t, denoted by Ω_t. This set contains all relevant information for forecasting the distribution of future cash flows, including state variables of the firm (capital and other stocks). It may include publicly available elements of the information sets of other firms, thus allowing for strategic interaction. Let $\pi(I_t, \Omega_t)$ denote cash flow, defined as operating profits minus all costs associated with investment I_t (including the cost of formulating, revising and implementing investment plans). An investment program consists of a sequence of random variables representing current and future investment flows, $\{I_{t+k}\}_{k=0}^{\infty}$. The optimal investment program maximises the expected present value of cash flows, and the value function $V(\Omega_t)$ satisfies the Bellman equation

$$V(\Omega_t) = \max \quad \pi(I_t, \Omega_t) + \delta E[V(\Omega_{t+1}) \mid \Omega_t] \tag{1}$$

where δ is the discount factor. The optimal program is represented by the following function

$$I^*_{t+k} = F(\Omega_{t+k}) \tag{2}$$

The investment function $F(\Omega)$ may be nonlinear. Let $I_{t,k}$ denote the investment planned in period t for period $t+k$, which we call the k-span investment plan. Because Ω_{t+k} must be forecasted in t, the function in (2) induces a probability distribution on $I_{t,k}$. In the survey data, firms report point estimates (not distributions) for planned investment. We assume that the k-span investment plan reported by the firm, $I^r_{t,k}$, corresponds to the conditional expectation of its optimal investment, given the current information set:

$$I^r_{t,k} = E(I_{t,k} \mid \Omega_t) \tag{3}$$

Define the k-span investment revision as the percentage difference between the current investment plan for k-periods ahead and last period's investment plan for $k+1$ periods ahead:

$$yk_t = (I^r_{t,k}/I^r_{t-1,k+1}) - 1 \tag{4}$$

This revision represents the updating of planned investment expenditures for a given target date. Since $\Omega_{t-1} \subset \Omega_t$, we get

$$E(yk_t \mid \Omega_{t-1}) = 0. \tag{5}$$

This is the key result: each k-span investment revision is a martingale.[2] Therefore, data on investment revisions provide direct evidence on the news in the information set Ω_t. This property characterises all revision processes under rational expectations. We do not need any assumptions about the structure of the investment function, such as linearity or adjustment lags in actual or planned investment.

The martingale property is based on the assumption that decision rule exploits all available information efficiently. Apart from that, however, we do not need any assumption about the particular form of the optimisation generating the investment function. For example, if investment is liquidity constrained, the optimal program is the sequence of investment plans that maximises the expected present value of net cash flows, subject to the constraint that planned investment is no larger than the cash flow (or stock) in each period. The values of $I_{t,k}$ will obviously differ from the unconstrained case, but the martingale property of investment revisions will be preserved as long as the value $I^r_{t,k}$ reported by the firm corresponds to the constrained investment profile.[3]

The martingale property of investment revisions is similar, but not identical, to the seminal result in Hall (1978) that optimal consumption behaviour under rational expectations and perfect capital markets implies that the marginal utility of consumption should be a martingale. If marginal utility is linear, changes in the level of consumption represent news in permanent income or the interest rate (but not in general - Kotlikoff and Pakes, 1978). Optimisation models with imperfect capital markets and liquidity constraints have been used to explain the observed cross-sectional and time-series properties of consumption changes, which often violate the martingale property (Hall and Mishkin, 1982; Zeldes, 1989; Altug and Miller, 1990; Hayashi, Altonji and Kotlikoff, 1996). The martingale property for investment revisions is more general because it does not require functional form or perfect capital market assumptions. But this comes at a cost – it requires that we have information on investment plans of the firm, not just the actual investment flows. If micro data were available on consumption plans (or other decisions by households or firms), analogous tests could be used to study the structure of shocks driving those decisions.

The martingale property does not require the assumption that the investment program maximises the value of the firm. If it does, however, then changes in the

[2] In their study of labour turnover Davis and Haltiwanger (1990), and most subsequent work in the area, measure the change in employment in period t relative to the *average level* of employment in $t-1$ and t, rather than the conventional way relative to t. They do this in order to treat new entry and exit symmetrically. The analogue here would be to define $zk_t = 2(I_{t,k} - I_{t-1,k+1})/(I_{t,k} + I_{t-1,k+1})$. But this does not work for investment revisions because the martingale property no longer holds - $E(zk_t \mid \Omega_{t-1}) \neq 0$.

[3] Of course the shadow price of capital differs in the two cases. Under liquidity constraints the shadow price satisfies the Euler condition (Bond and Meghir, 1990): $\lambda_t = (1+\mu_t)\partial\pi/\partial K_{t-1} + (1-\delta)\beta E_t \lambda_{t+1}$, where $\mu > 0$ is the shadow price of funds, δ is the capital depreciation rate and β is the discount factor. The constrained shadow price of capital exceeds the unconstrained value.

firm's stock market value provide an additional indicator of the news in Ω_t (Pakes 1985). Let R denote the one-period excess rate of return on the firm's equity. For empirical purposes, we use $R = (\Delta P_t + D_t)/P_{t-1} - r_t$ where ΔP is the calendar year change in the stock price (adjusted for splits), D is calendar year cash dividends and r is the Aaa corporate bond rate. Under a (linear) no-arbitrage condition, R represents the percentage change in the expected value of the firm associated with the news in Ω_t :

$$R_t = \frac{V(\Omega_t) - E[V(\Omega_t) \mid \Omega_{t-1}]}{E[V(\Omega_t) \mid \Omega_{t-1}]}. \tag{6}$$

We emphasise that R is *not* the same as Tobin's-Q (either marginal or average). Tobin's-Q is the marginal market value of capital (relative to replacement cost), whereas R is the unanticipated change in market value due to new information. We can use R as an indicator of news in Ω without the standard assumptions needed to justify the use of average Tobin's-Q in the investment function (linear homogeneity in the profit and adjustment cost functions, perfect competition in input and product markets, and strong efficiency in the stock market). In the stochastic specification for R, we will also allow for non-fundamental movements in stock market prices (see Section 5).[4]

3 Description of the Data

The data are based on annual surveys conducted by the McGraw-Hill Company during the period 1949-1973 (for details, see Eisner 1978). The original panel contains information for about 700 firms on current investment and annual, planned investment expenditures over a four year horizon. The survey question was: "How much do you now plan to invest in new plant and equipment one, two, three and four years ahead?" Assuming that firms report investment plans in future (target date) prices, we deflate the reported investment planned in year t for k years ahead, $I_{t,k}$, by the price index for investment goods for year $t + k$.[5] From these data we extract a subset of firms based on two requirements: that the firm can be identified by name and that there be at least one observation on the zero-span revision. The firm name was used to match the investment data to financial information from the Center for Research on Stock Prices (CRSP) to construct the one-period rate of return, and to Standard and Poor's Compustat data for other firm-specific variables used in Sections 4 and 8. The

[4] Given the asset mix of the firm, R is approximately equal to the change in Tobin's-Q. "Non-fundamental" variation in R does not cause a problem here (provided that covariance stationarity is preserved) because it can be modelled as measurement error in R, which is an endogenous variable (an indicator of news in Ω).

[5] Deflating by current prices does not affect the results.

final sample contains 318 firms, 229 in manufacturing and 89 in non-manufacturing (Appendix 2 for details). The sample accounts for 21 percent of sales and 24 percent of capital investment in the United States in 1967.[6] The typical firm is large: median (mean) levels of investment and sales are \$42 million (\$113 m) and \$697 million (\$1723 m) in 1976 dollars.

Data on investment expenditures and one-year ahead plans are available for 1949-1973, but longer span investment plans only cover 1958-1973. Since firms do not report plans for all investment spans or years, the panel is unbalanced. We assume that sample selection is unsystematic (i.e., unrelated to the realisation of the shocks). A probit analysis shows that the probability of non-reporting in any given year is inversely related to the firm's level of sales, which is not surprising but, more importantly, it is not related to the size of the mean revision at the sector or aggregate level. There were many missing observations in the original data set, but no cases where the firm reported zero levels of actual or planned investment.[7]

The McGraw-Hill surveys were distributed in March of each year and completed by firms shortly thereafter. Thus the investment revisions we construct from these plans for year t should reflect news that accumulated between March or April in years $t-1$ and t. However, the stock market rate of return is computed on a calendar year basis. We test the implications of this information structure in Section 4, and incorporate it into the factor model in Section 5.

Panel A in Table 2 presents descriptive statistics for investment revisions and R.[8] There are about 140 firms in the sample per year, and between six and eleven annual observations on investment revisions per firm (varies with investment span). The mean revisions (averaged over all firms and years) indicate that firms slightly overestimate investment expenditures one-year ahead, but underestimate them over longer horizons. Firms revise longer span investment plans upward as the target date approaches. The different spans of investment revisions are positively correlated (Panel B), as one would expect if they represent news in Ω. But the fact that these correlations are less than one also indicates the presence of some independent measurement error. In Section 5 we use a factor model to estimate both the structural variance (news in Ω) and measurement error variance.

[6] Coverage varies by sector. The sample includes about 33 (35) percent of investment (sales) in manufacturing, but only 10 (16) percent in non-manufacturing. Aggregate investment data are taken from the U.S. Survey of Current Business, and sales data from the Economic Report of the President.

[7] We know from the work of Caballero and others that investment is lumpy and discontinuous at the *plant* level, but we do not see this at the level of the *firm* in this sample.

[8] We dropped observations on investment revisions that were larger than 300 percent (in absolute value). These deletions constitute between 0.4 and 1.5 percent of the sample (varies by investment span). This affects only the correlations of investment revisions with R (not between the revisions). Correlations with R are between 150 and 250 percent larger after the deletions, which strongly indicates that deleted outliers are contaminated with measurement error.

The martingale property implies that the mean investment revision over time should be zero (cross sectional means for a given year will reflect common shocks and thus may differ from zero). In the sample, the mean investment revision is not significantly different from zero for between 65 and 85 percent of the firms (varies with investment span). The deviations from zero in the mean investment revisions in Panel A suggest that the *reported* investment plans contain a "budgeting bias" – reported plans are likely to be lower than actual expenditures because they only include items budgeted by the survey date. On the assumption that the true revisions are a martingale (see Section 4), we can infer the budgeting bias from the mean revisions in Panel A.[9] This procedure yields the following implied ratios of planned investment to actual investment, say $b_k = I^r_{t,k}/I_{t+k}$ for span $k : b_1 = 1.04$, $b_2 = 0.86$, $b_3 = 0.74$ and $b_4 = 0.64$. As expected, the budgeting bias increases with the span k. Finally, the mean of R in Panel A is consistent with an equity risk premium, though it is somewhat higher than the average *ex post* premium in the U.S. during 1949-73 (7.1 percent).

4 Martingale Tests

To test the martingale property, we regress investment revisions for each span against firm-level information known at the time the investment plans were formulated. Given the information structure, the revisions in year t can be correlated with information known in calendar year $t-1$ but not for higher order lags. To conduct this analysis, we matched information from Compustat to the investment survey data. The merged data set contains about ninety percent of the original firms for the abbreviated period 1954-73. We include in the information set three lagged values of gross investment, sales, cash flow, employment, a measure of variable input cost and a set of time dummies.

Panel A in Table 2 summarises the test statistics of the null hypothesis that the investment revisions are unrelated to the second and third lags of the variables in the information set. The results strongly confirm the martingale property of investment revisions, and this holds for alternative definitions of the information set.

By itself, this does not prove that investment revisions actually reflect news in Ω. The martingale property would hold if investment revisions were pure noise. But if they are noise, the revisions should not be correlated with R. However, if investment revisions and R contain news in Ω (perhaps contaminated by measurement error), they should be correlated. Let θ denote the fraction of the calendar year elapsed by the time surveys are completed. The investment revision in t should reflect fraction

[9] Define the budgeting bias for firm i and span k as $b_{ik} = I^r_{i,t,k}/I_{i,t+k}$. Then the reported k-span revision is $yk^r_{it} \simeq yk_{it} + [\eta_{ik} \text{ -} \eta_{i,k+1}]$. In the empirical work we assume that this bias between any two investment spans is common to all firms.

θ of the news during calendar year t and $(1-\theta)$ of the news in $t-1$. Thus each k-span revision in t should be correlated with R_t and R_{t-1} but not with leading values or higher order lags of R. A consistent estimate of θ is $\delta/(1+\delta)$ where $\delta = cov(yk_t, q_t)/cov(yk_t, q_{t-1})$. Given the information structure, we expect θ to be on the order of 1/2 (i.e., surveys completed by June).

The autocorrelation structure between revisions and R strongly supports the hypothesis that investment revisions contain news in Ω (Panel B, Table 2). In addition, the estimates of θ are consistent with the timing of the surveys, and are similar across investment spans as we would expect.

5 Specification of the Factor Model

We decompose the news in Ω into three nested (uncorrelated) components: a micro shock u_{ijt}, a sector shock e_{jt}, and an aggregate shock v_t. In addition to these shocks to the information set, we allow for the reported investment revisions to contain measurement error, denoted by z^k_{ijt} for span k. We also allow for the firm's stock market rate of return, R, to contain variation that is unrelated to the news in Ω. This "non-fundamental" component of R is denoted by u'_{ijt} at the micro level, e'_{jt} at the sector level, and v'_t at the aggregate level.

Given the information structure of the surveys, we write the factor model as

$$\begin{aligned} R_{ijt} &= v_t + e_{jt} + u_{ijt} + v'_t + e'_{jt} + u'_{ijt} \quad (7) \\ Ryk_{ijt} &= \theta(\alpha_k v_t + \beta_k e_{jt} + \gamma_k u_{ijt}) \\ &\quad +(1-\theta)(\alpha_k v_{t-1} + \beta_k e_{j,t-1} + \gamma_k u_{ij,t-1}) + z^k_{ijt} \quad (8) \end{aligned}$$

where $k \in (0,3)$ and $z^k_{ijt} = \eta^k_{ijt} - \eta^{k+1}_{ij,t-1}$ and η^k_{ijt} is the measurement (reporting) error in the k-span investment plan. We normalise by setting the coefficients equal to unity in the R equation (i.e., by defining each component in terms of a one-percent change in market value). In addition, we include the lagged version of equation (7) in the model. Given the information structure, this equation is needed to identify the parameter θ.

Identification of the model comes from the multiple levels of aggregation and from the assumption that the shocks are identically distributed. At each level, the model generates a theoretical covariance matrix that depends on the underlying parameters. To illustrate, we first take deviations of the micro-level variables around the sector/year means in (7) and (8) and obtain:

$$\begin{aligned} R_{ijt} - R_{..jt} &= u_{ijt} + u'_{ijt} \quad (9) \\ yk_{ijt} - yk_{..jt} &= \theta\gamma_k u_{ijt} + (1-\theta)\gamma_k u_{ij,t-1} + z^k_{ijt} \quad (10) \end{aligned}$$

These equations, together with the lagged version of equation (9), generate the following theoretical covariance matrix:

$$\Sigma_m = \begin{array}{llllll} \sigma_u^2+\sigma_{u'}^2 & & & & & \\ \phi_m & \sigma_u^2+\sigma_{u'}^2 & & & & \\ \theta\gamma_0\sigma_u^2 & (1-\theta)\gamma_0\sigma_u^2 & \psi\gamma_0^2\sigma_u^2+\sigma_0^2 & + & & \\ \theta\gamma_1\sigma_u^2 & (1-\theta)\gamma_1\sigma_u^2 & \psi\gamma_0\gamma_1\sigma_u^2+\sigma_{01} & \psi\gamma_1^2\sigma_u^2+\sigma_1^2 & & \\ \theta\gamma_2\sigma_u^2 & (1-\theta)\gamma_2\sigma_u^2 & \psi\gamma_0\gamma_2\sigma_u^2+\sigma_{02} & \psi\gamma_1\gamma_2\sigma_u^2+\sigma_{12} & \psi\gamma_2^2\sigma_u^2+\sigma_2^2 & \\ \theta\gamma_3\sigma_u^2 & (1-\theta)\gamma_1\sigma_u^2 & \psi\gamma_0\gamma_3\sigma_u^2+\sigma_{03} & \psi\gamma_1\gamma_3\sigma_u^2+\sigma_{13} & \psi\gamma_2\gamma_3\sigma_u^2+\sigma_{23} & \psi\gamma_3^2\sigma_u^2+\sigma_3^2 \end{array}$$

where $\phi_m = E(u'_{ijt}, u'_{ij,t-1})$, $\psi = \theta^2 + (1-\theta)^2$ and we assume covariance stationarity (tested and accepted, see below). There are 21 covariances and only 19 parameters, but it is easy to verify that the model is not identified without further restrictions on the covariances between the measurement errors in the investment plans, the terms denoted by σ_{kl} in Σ_m $(k, l \in (0, 3)$.[10] We assume that there is a common covariance between the reporting errors in any two spans of investment plans - i.e, $\sigma_{kl} = E(\eta^k_{ijt}, \eta^l_{ijt}) = \rho$. We experimented with other specifications that allow the covariance to differ for various sets of investment spans, but the main results are very similar (for more discussion, see Section 6). Under this assumption, it can be verified that there are eight over-identifying restrictions.

The sector and aggregate equations can be analysed in a similar way. At the sector level, we focus on the deviations around the year means – $R._{jt} - R_{..t}$ and $yk_{ijt} - yk_{..t}$. At the aggregate level, we use $R_{..t} - R_{...}$ and $yk_{..t} - yk_{...}$. Unlike the micro level, we do not need to allow for covariances between measurement error in investment plans at the sector and aggregate levels (the null hypothesis that they are zero is not rejected). Also, as specified above, the data indicate serial correlation in the non-fundamental error at the micro and aggregate levels, so we allow $E(u'_{ijt}, u'_{ij,t-1}) = \phi_m$ and $E(\nu'_t, \nu'_{t-1}) = \phi_a$. Finally, we tested the hypothesis that the non-fundamental variance in the stock market rate of return is stationary - i.e., $\sigma^2_{v'_t} \neq \sigma^2_{v'_{t-1}}$, $\sigma^2_{e'_t} \neq \sigma^2_{e'_{t-1}}$ and $\sigma^2_{u'_t} \neq \sigma^2_{u'_{t-1}}$. We cannot reject this hypothesis at any level of aggregation.

As noted earlier, we also use the identifying assumption of identically distributed shocks. Without it, we could not express the theoretical covariance matrix in the simple form given above. The underlying (martingale) theory of investment revisions implies that the shocks must be serially uncorrelated, but it does not require homoskedastic shocks. However, since we are analyzing investment revisions expressed in percentage terms, we think it is reasonable to assume that the variances of the (micro) structural shock and of the measurement error are independent of the size of the firm.

[10] This is due to the non-linear way in which parameters enter the model. The structural parameters are $(\theta, \sigma^2_u, \gamma_0, \gamma_1, \gamma_2, \gamma_3)$, and measurement error parameters are $(\sigma^2_{u'}, \sigma^2_0, \sigma^2_1, \sigma^2_2, \sigma^2_3, \sigma^2_0, \phi_m)$ and $(\sigma_{01}, \sigma_{02}, \sigma_{03}, \sigma_{12}, \sigma_{13}, \sigma_{23})$.

Given the specifications described above, there are twelve over-identifying restrictions at the sector level and ten at the aggregate level. The model is estimated by maximum likelihood.

6 Empirical Results

Table 3 summarises the parameter estimates for the factor model. We first test the over-identifying restrictions. At the micro-level these are rejected at conventional levels of significance (χ^2_8= 45.6). However, since the sample is large it is not surprising that a conventional test, with a fixed level of significance, is rejected. As an additional check, we use the alternative measure of the critical value for a convention F-test proposed by Leamer (which we call the Bayesian-F). This test has the property that, given a diffuse prior distribution, the critical value is exceeded only if the posterior odds favor the alternative hypothesis.[11] Using the Bayesian-F, we do not reject the restrictions at the micro level – the F-statistic is 5.7, well below the critical value of 9.5. At the sector level, the over-identifying restrictions are not rejected by conventional criteria (χ^2_{12} = 8.8, p-value =.55). The restrictions are rejected at the aggregate level (χ^2_{10}= 32.45), but the test is not very informative given the small sample in the time dimension ($n = 25$).[12]

These test statistics indicate that there may be some remaining misspecification in the model. As discussed later in this section, we experimented with less restrictive stochastic specifications, but both the test results and the variance decomposition of investment revisions and the stock market rate of return were similar.

Turning to the parameter estimates, the zero-span investment revision does not respond to structural shocks – the estimates of α, β and γ for $k = 0$ are not statistically significant. This is not surprising, since it may be very costly to change and implement investment plans at such short notice (less than one year). However, investment revisions for higher spans do respond to these shocks at each level of aggregation. The point estimates of the response parameters are statistically significant, and broadly similar across investment spans, but the precision falls off sharply at the aggregate level (the relevant sample size in that dimension is very small). The signal rates for investment revisions (the ratio of structural to total variance) confirm that revisions of reported investment plans are very noisy, but they clearly contain value-relevant information. As shown by σ^2_u, about 4.7 percent of the micro-level variation in R is

[11] The Bayesian-$F = (T/k)(T^{p/T} - 1)$ where T is the sample size, $T - k$ is degrees of freedom, and p is the number of restrictions being tested (Leamer, 1978, Chap.4).

[12] The reported test statistics are from the model where the parameter θ is not constrained to be the same at each level of aggregation. The point estimates (standard errors) of θ at the micro, sector and aggregate levels are .60 (.07) , .75 (.15) and .33 (.37) respectively. The pooled estimate, given in Table 3, is .53 (.03).

"fundamental" (i.e., related to changes in investment plans). This is quite similar to independent estimates by Pakes (1985), Lach and Schankerman (1989) and others from dynamic factor models of physical capital and R&D investment. The point estimates of the signal rates for R at the sector and aggregate levels are marginally higher (σ_e^2 and σ_v^2). Due to the small sample in the time dimension, however, the standard error on the point estimate of σ_v^2 is large.

We can use the parameter estimates to decompose the *structural variance* in investment revisions and stock market rate of return into micro, sector and aggregate components. We focus on the structural variance because the 'measurement error' in investment revisions is (probably exclusively) idiosyncratic, and not of any economic interest. The micro variance is given by $\gamma_k^2\sigma_u^2$, the sector component by $\beta_k^2\sigma_e^2$ and the aggregate component by $\alpha_k^2\sigma_\nu^2$. For the stock market rate of return, the coefficients α, β and γ are normalised to unity.

Table 4 presents the percentage decomposition for each investment span and for R, using the parameter estimates from Table 3. Micro shocks only account for about 10-25 percent of the structural variance in investment revisions. Sector shocks account for about another 35 percent, with macro shocks taking about 50 percent. This decomposition is similar for each of the four investment spans (except the zero-span revision, which is basically noise). The stock market rate of return, R, is driven roughly equally by micro, sector and aggregate shocks. If we took a very skeptical view, and treated the point estimate of σ_ν^2 as not significantly different from zero, then of course the aggregate component would vanish. In this case, micro shocks would account for 26-44 percent of the structural variance in investment revisions, and 44 percent in the stock market rate of return. Even then, idiosyncratic shocks do not appear to be the dominant source of investment risk.

We conduct senstivity analysis of the central result to relaxing various restrictions. Beginning with the baseline specification in Section 5, we experimented with five less restrictive models. First, we allow the parameter θ to differ at each level of aggregation. Such differences could arise if news at the micro, sector and aggegate level have different time distributions within a year (since different amounts of information will have arrived by the time firms complete the surveys). Second, we allow the shocks to the information set to be non-stationary at each level of aggregation - i.e. $\sigma_{v_t}^2 \neq \sigma_{v_{t-1}}^2$, $\sigma_{e_t}^2 \neq \sigma_{e_{t-1}}^2$and $\sigma_{u_t}^2 \neq \sigma_{u_{t-1}}^2$. Third, we allow for first-order serial correlation between the shocks to the information set, at each level of aggregation. Fourth, we allowed the *non-fundamental* component of the stock market rate of return to be non-stationary at each level of aggregation - i.e., $\sigma_{v_t'}^2 \neq \sigma_{v_{t-1}'}^2$, $\sigma_{e_t'}^2 \neq \sigma_{e_{t-1}'}^2$and $\sigma_{u_t'}^2 \neq \sigma_{u_{t-1}'}^2$. Fifth, we allow a different (common) covariance among the measurement errors in the zero-span revision and those of spans $k > 0$ ($\sigma_{0k} = \sigma'$ and $\sigma_{jk} = \sigma$ for $j, k > 0$). We try this specification because the parameter estimates in Table 3 indicate that, unlike the other investment revisions, the zero-span revision is essentially noise – the response parameters to the structural shocks are not statistically significant.

For each of these specifications, we re-estimated the model and computed the corresponding decomposition of the structural variance in investment revisions. The results were very similar to those reported in Table 4 (not reported, for brevity). The micro component was marginally smaller when we relax these restrictions (typically, by one or two percentage points). The micro component noticeably increased only when we changed the specification of the measurement errors. In that case, the micro component accounted for 4.8% of the structural variance for the zero-span revision ($k = 0$), 24% for $k = 1$, 30.3% for $k = 2$ and 27.6% for $k = 3$.

We conclude from this sensitivity analysis that the central finding in this paper - that idiosyncratic shocks are not the main source of investment risk - appears to be robust to the specification of the factor model, despite the formal rejection of the overidentifying restrictions in the baseline model using conventional testing criteria.

Micro shocks appear to be much less important for investment revisions than might be suggested by the literature on plant-level heterogeneity in labor turnover and productivity (e.g., Davis and Haltiwanger, 1990; Davis, Haltiwanger and Shuh, 1997; Roberts, 1995) and in plant and equipment investment (Doms and Dunne, 1993; Caballero, Engel and Haltiwanger, 1995; Caballero, 1998). This is so, even if we were to treat sector shocks as reflecting micro variation, due to the relatively small number of firms in some sectors (see Appendix). Our analysis differs from the existing literature in two relevant respects. First, we focus on heterogeneity at the firm rather than the plant level. One would expect to find a larger role for micro shocks at the plant level. The second difference is that we focus directly on the structure of the *shocks* driving investment by examining revisions in investment plans. All previous studies focus on the structure of *observed changes* in investment (or employment), which will differ from the shocks unless investment is a random walk. If adjustment of investment to different types of shocks varies, the decomposition based on observed changes in the level of investment might be quite different. This makes direct comparison difficult. However, a decomposition of the variance in the percentage change in actual investment for firms in this sample supports our conjective - the micro variance of actual changes in investment expenditures is much larger than when we decompose the shocks directly, using investment revisions.[13]

[13] The within-firm (micro) variance of the actual change in log investment accounts for about 73 percent of the total variance. The sector and aggregate variances account for 19 and 8 percent, respectively. Part of the micro variance may be due to measurement error in investment *expenditures*, but we would not expect it to be very large.

7 Heterogeneity in Micro Responses

In this section we examine whether part of the micro variation in investment revisions is due to heterogeneous micro responses to aggregate shocks. If the micro responses vary across firms, then the *effect* of an aggregate shock on investment revisions will also differ across firms, and would be wrongly interpreted as micro variance. If micro responses vary, then the observed cross-sectional (within-industry) variance should increase with the size of the aggregate shock. Under the maintained hypothesis that the underlying shocks are covariance stationary, we can use the observed non-stationarity in the cross sectional variance of investment revisions to identify the dispersion of micro response parameters.

We follow notation in Section 5 but, for simplicity, we write investment revisions in terms of a micro shock and a single common shock as

$$yk_{ijt} = \theta(\beta^*_{ki} e_{jt} + \gamma_k u_{ijt}) + (1-\theta)(\beta^*_{ki} e_{j,t-1} + \gamma_k u_{ij,t-1}) + z_{ijt} \tag{11}$$

where β^*_{ki} is the response of the $k-$span investment revision for firm i to the common shock, and $\{e, u, z\}$ are *iid* normal variables with zero mean. Define $\beta^*_{ki} = B_k + \beta_{ki}$, and assume that $\{\beta_{ki}\} \sim N(0, \Omega)$ where Ω may be non-diagonal.[14] This model implies the following *cross-sectional* variance for investment revisions, conditional on industry and year:

$$V(yk \mid j,t) = \sigma^2_z + \gamma^2_k \sigma^2_u \{\theta^2 + (1-\theta)^2\} + \sigma^2_\beta \{\theta e_{jt} + (1-\theta) e_{j,t-1}\}^2 \tag{12}$$

To eliminate dependence on the unobserved shock, e_{jt}, we use (11) to get plim $yk_{.jt} = B_k\{\theta e_{jt} + (1-\theta)e_{j,t-1}\}$, and then substitute into (12) to obtain

$$V(yk \mid j,t) = \{\sigma^2_z + \gamma^2_k \sigma^2_u \ (\theta^2 + (1-\theta)^2)\} + (\sigma_\beta / B_k)^2 \ yk^2_{.jt} \tag{13}$$

The slope parameter in (13) identifies the coefficient of variation in micro responses. The intercept captures both measurement error in revisions, σ^2_z, and the genuine micro variance $\gamma^2_k \sigma^2_u \ (\theta^2 + (1-\theta)^2)$. The overall micro-level structural variance is $V_M = \sigma^2_\beta \sigma^2_e + \gamma^2_k \sigma^2_u$, which includes both the variance due to heterogeneity and the genuine micro variance. We can write the *proportion* of the micro-level structural variance that is accounted for by heterogeneity as $V_H/V_M = \sigma^2_\beta \sigma^2_e / (\sigma^2_\beta \sigma^2_e + \gamma^2_k \sigma^2_u)$. Using estimates of σ_β / B_k, and γ_k and B_k from Section 6, we can back out an estimate of V_H/V_M.

Table 5 presents the parameter estimates of equation (13).[15] We can easily reject the hypothesis that response parameters are the same across firms. The slope coefficients are statistically very significant and similar across investment spans. There is

[14] We assume that the covariance matrix Ω is the same for all sectors, but the conclusions are not sensitive to this assumption.

[15] The nonlinear least squares parameter estimates in the table are not fully efficient because they do not exploit the potential covariance between the micro response parameters of a given firm in different equations.

substantial heterogeneity in the micro responses of investment revisions to common shocks: the standard deviation in micro parameters is as large as the mean response. Moreover, this heterogeneity accounts for nearly three-quarters of the micro structural variance in investment revisions (last row in the table).[16]

To summarise these results, we find that less than a quarter of the structural variance in investment revisions is "micro variance," and that nearly three-quarters of that is actually due to the fact that firms react differently to aggregate shocks. On these computations, "genuine" micro shocks account for only a small fraction of the overall structural variance (e.g., 0.25 x 0.25=0.06). This finding suggests that firms in this sample were quite successful at diversifying idiosyncratic risk, but large variation in firm-specific response parameters to aggregate shocks creates the appearance of large micro risk.

8 Determinants of Investment Revisions

In this section we examine the empirical determinants of investment revisions and the stock market rate of return at the firm level. This analysis confirms that revisions reflect (estimated) news in variables that figure prominently in the capital investment literature: demand, cash flow and factor prices. We use undeflated sales to measure demand (time dummies are also included). We use a measure of average variable cost as a crude measure of factor prices.[17] To construct estimates of news, we estimate a second-order vector autoregression in the logs of sales, factor prices and cash flow, and then use the *residuals* from these regressions as measures of news. We then regress investment revisions of each span and R on current and lagged values of these residuals (Table 6). The data on sales, cost and cash flow are reported by fiscal year, while R is measured by calendar year and investment revisions by the survey dates. Thus investment revisions and R should be correlated with current and possibly one lagged value of news. The results confirm this prediction (see test statistics $T1$and $T2$ in the table).

The parameters represent elasticities of investment plans with respect to news in the variables. Investment revisions are positively related to news in sales and negatively to news in factor prices, as expected. The implied sales elasticity of investment plans is lower than the value of unity implied by constant returns to scale. The coefficient on sales news is similar across investment spans, indicating that its effect on investment plans is not transitory. These findings are consistent with the large liter-

[16] This computation uses the sector-level response parameters from Table 3. If the aggregate-level parameters are used, V_H/V_M rises marginally.

[17] This is measured as the ratio of total variable costs (reported in Compustat) to sales. Variations in average variable cost may also reflect fluctuations in capacity utilisation, if labour is a quasi-fixed input.

ature on investment. Investment revisions are positively related to news in cash flow, except for the zero-span where changes may be hard to make (this is consistent with our findings from the factor model). As expected, the stock returns are positively related to cash flow, and negatively to factor prices (surprisingly, not to sales news).

The r^2's in these regressions are low, but they are not an informative measure of fit because of the measurement error in investment plans and stock market rate of return. As a more meaningful measure of fit, we compute the fraction of the *covariance* between investment revisions and R that is accounted for by the regressors, which we denote by f in the table. The estimates of the news in sales, factor prices and cash flow account for between a third and half of this covariance at the firm level.

The covariance between revisions and news in cash flow does not show that investment plans are liquidity constrained, since the news may reflect unobserved heterogeneity in investment demand. To test for liquidity constraints, the standard procedure is to check whether the response of investment to cash flow is higher for firms that are more likely, on *a priori* grounds, to be liquidity constrained – e.g., firms that pay low or no dividends (Fazzari, Hubbard and Petersen (FHP), 1988). In this section we apply the FHP approach to investment *revisions* and *news* in cash flow, which has not been done previously.

We conduct two tests. The first examines whether the response parameter of investment revisions to news in cash flow in year t, say β, is larger if the firm pays no dividends in that year. This test is implied by a strict interpretation of a hierarchy of finance based on asymmetric information, where the firm uses neither equity nor debt to finance new investment (Bond and Meghir, 1994). Let $\beta = \beta_0 + \beta_1 Z$ where $Z = 1$ if the firm pays dividends in a year and zero otherwise. We test the null hypothesis $\beta_1 = 0$ against the alternative $\beta_1 > 0$. The second test examines whether the response of investment revisions to news in cash flow depends on the firm's dividend payout ratio. Each firm is assigned to one of four groups based on its average dividend payout ratio, D : less than 10 percent, 10-20 percent, 20-40 percent and greater than 40 percent. We test the null hypothesis that β is the same for each group, against the alternative that β is larger for lower payout firms.[18]

Table 7 presents the test statistics. There is no evidence, in either test, that the response of investment revisions to news in cash flow is any greater for firms that do not pay dividends or that have low dividend payout ratios.[19] This finding

[18] The numbers of firms in each dividend payout group (starting with the lowest) are 13, 37, 138 and 85. An assignment based on the firm's average payout ratio may be sensitive to fluctuations in earnings, since dividends are stable. We also tried an assignment rule requiring that at least 50 percent of a firm's dividend payout rates fall within a given interval (66 could not be assigned and were dropped). The results are similar to those reported in the text.

[19] We also tried two other variants: grouping firms according to size rather than dividend payout ratio, which is more consistent with a hierarchy of finance based on fixed transaction costs; and allowing the investment response parameter to differ in recession years, since firms may be more sensitive to cash flow in tight credit markets. There was no evidence of liquidity constraints in

differs sharply from earlier empirical studies of investment liquidity constraints. Part of the reason may be that we study how revisions in investment plans respond to news in cash flow, whereas earlier studies relate the level of investment to the level of cash flow. It may be harder to detect the nonlinear responses implied by liquidity constraints if there is measurement error in estimates of the news in cash flow. In addition, the firms in our sample are quite large, and are thus less likely to be liquidity constrained. However, our finding is consistent with a number of more recent studies that use methodology similar to FHP and find evidence against liquidity constraints (Caballero, 1998, for a review). In addition to these dissenting empirical studies, Kaplan and Zingales (1997) argue that, from a theoretical perspective, greater sensitivities of investment to cash flow cannot be interpreted as evidence that firms are more financially constrained.

9 Concluding Remarks

This paper shows that micro shocks are not the dominant source of risk in investment decisions, at least for the medium to large firms in our sample. We use a factor model to analyse revisions in investment plans, and exploit the stock market rate of return at the firm level to distinguish between value-related shocks and reporting (or measurement) error in investment revisions. We find that micro shocks account for less than 25 percent of the structural (value-related) variance in revisions. Moreover, we show that as much as three-quarters of this "micro variance" is actually due to heterogeneity in firm-level responses to aggregate shocks.

From a methodological perspective, this paper shows that microeconomic data on *plans* can be useful for studying the structure of risk faced by agents. The relative importance of micro and common shocks is likely to depend on the type of economic decision, the characteristics of the agent, and the policy environment. To study these issues, the approach that exploits the martingale property of revisions in plans could be applied to micro-level data on investment, consumption and other plans for more recent periods and in different countries.

either test.

Table 1. Descriptive Statistics[a]

Panel A. Investment Revisions and the Stock Market Rate of Return

	Investment Span/Market Return				
	$k = 0$	$k = 1$	$k = 2$	$k = 3$	R
No. firms	142	140	130	123	160
No.observations	3424	2109	1952	1843	4015
Mean	-.040	.195	.151	.137	.093
(std.error)	(.006)	(.011)	(.010)	(.011)	(.005)
Median	-.078	.095	.041	.020	.055

Panel B. Correlation Among Investment Revisions[b]

	$k = 0$	$k = 1$	$k = 2$
$k = 1$	.259*		
$k = 2$	.197*	.543*	
$k = 3$	.236*	.454*	.688*

Notes:

[a]The k-span investment revision is $I_{t,k}/I_{t-1,k+1} - 1$. The stock market rate of return is defined as $R = (\Delta P_t + D_t)/P_{t-1} - r_t$, where ΔP is the calendar year change in the stock price (adjusted for splits), D is calendar year cash dividends and r is the Aaa corporate bond rate.

[b]An asterisk denotes significance at the 0.01 level.

Table 2. Martingale Tests and Information Content of Investment Revisions

Panel A: Martingale Tests

	Investment span			
	$k = 0$	$k = 1$	$k = 2$	$k = 3$
Variables in Information Set				
Investment	0.39	0.51	$<.001$	0.22
	(.68)	(.60)	(.99)	(.80)
Sales, cash flow, factor cost	0.89	0.38	0.61	0.65
	(.50)	(.89)	(.72)	(.69)
Investment, sales, cash flow,	1.30	0.63	1.04	0.57
factor cost, employment	(.22)	(.79)	(.40)	(.84)

Panel B: Autocorrelations between Investment Revisions and R

	Investment Span			
	$k = 0$	$k = 1$	$k = 2$	$k = 3$
Correlation with:				
R_t	.072*	.173*	.152*	.130*
R_{t-1}	.088*	.144*	.111*	.084*
R_{t-2}	.011	-.013	.027	.011
R_{t-3}	.011	.008	.009	-.022
R_{t+1}	.052*	.009	.015	.010
R_{t+2}	-.025	.067*	.015	.010
R_{t+3}	-.013	.028	-.001	-.002
θ	0.45	0.55	0.58	0.61

Notes: In Panel A, investment revisions are regressed against three lagged values of the logs of variables and year dummies. Factor cost is total variable input costs divided by sales. Each cell reports the F-test (p-value) of the null hypothesis that coefficients on the second and third lags of all variables are zero. Number of observations is 1138.

In Panel B, the estimate of $\theta = \delta/(1+\delta)$ where $\delta = cov(yk_{ijt}, R_{ijt})/cov(yk_{ijt}, R_{ij,t-1})$. An asterisk denotes significance at the 0.01 level.

Table 3. Parameter Estimates for the Factor Model

	Investment Span			
	$k = 0$	$k = 1$	$k = 2$	$k = 3$
Micro Parameters				
γ	-.40	2.29	4.97	3.51
	(.25)	(.33)	(.65)	(.45)
$\sigma_u^2 = .047$ (.013)				
$\rho = .24$ (.029)				
$\phi_m = .055$ (.013)				
Signal rate (%)	.40	12.5	57.9	29.2
	(.11)	(3.5)	(16.0)	(8.1)
Sector Parameters				
β	.51	3.33	5.00	4.49
	(.32)	(.72)	(1.05)	(.94)
$\sigma_e^2 = .060$ (.025)				
Signal rate (%)	1.2	33.5	75.3	60.9
	(.75)	(7.24)	(15.8)	(12.7)
Aggregate Parameters				
α	2.30	4.47	5.63	4.48
	(1.34)	(2.19)	(2.70)	(2.32)
$\sigma_v^2 = .068$ (.085)				
$\phi_a =$ -.19 (.05)				
Signal rate (%)	5.9	18.2	68.7	95.0
	(3.4)	(8.9)	(32.9)	
$\theta = .53$ (.03)				

Notes: Estimated standard errors are in parentheses. The signal rate is the estimated ratio of structural variance to total variance.

Table 4. Variance Decomposition: Investment Revisions and Stock Market Rate of Return[a]

	Investment Span/Market Return				
	$k = 0$	$k = 1$	$k = 2$	$k = 3$	R
Decomposition of Structural Variance (%)					
Micro variance	1.9	10.8	24.1	17.3	26.9
Sector variance	5.7	29.3	31.2	36.2	34.3
Aggregate variance	92.4	59.9	44.7	46.5	38.8

Notes: Each cell gives the ratio of the estimated structural variance to total variance at the indicated level of aggregation. For example, the micro component for the k-span revision is $\gamma_k^2\sigma_u^2/(\gamma_k^2\sigma_u^2 + \beta_k^2\sigma_e^2 + \alpha_k^2\sigma_\epsilon^2)$. For R, the α, β and γ are normalised to unity. Computed using parameter estimates in Table 3.

Table 5. Heterogeneity in Mirco Responses: Investment Revisions

	Investment Span			
	$k=0$	$k=1$	$k=2$	$k=3$
Parameter				
Intercept	.048	.169	.134	.162
	(.008)	(.018)	(.019)	(.020)
σ_β/B	1.65	1.04	1.19	1.08
	(.045)	(.059)	(.062)	(.098)
r^2	.45	.23	.27	.11
n	388	259	256	251
% of micro variance due to heterogeneity	84.8	74.5	64.6	70.9

Notes: Based on nonlinear least squares estimation of equation (13) in the text. Estimated standard errors are in parentheses. The proportion of the micro variance that is due to heterogeneity is computed as $\sigma_\beta^2\sigma_e^2/(\sigma_\beta^2\sigma_e^2+\gamma_k^2\sigma_u^2)$.

Table 6. Empirical Determinants of Investment Revisions

and Stock Market Rate of Return[a]

	Investment Span/Market Return				
	$k = 0$	$k = 1$	$k = 2$	$k = 3$	R
Variable					
Factor prices (c)	-.21	-.68	-.80	-.20	-.80
	(.24)	(.45)	(.42)	(.41)	(.20)
Sales (s)	.50	.58	.62	.40	.08
	(.09)	(.18)	(.17)	(.16)	(.06)
Cash flow (π)	.01	.14	.14	.12	.15
	(.03)	(.05)	(.05)	(.05)	(.02)
c_{-1}					-.68
					(.19)
s_{-1}					-.18
					(.07)
π_{-1}					.02
					(.03)
r^2	.027	.031	.040	.022	.080
n	1143	1173	1073	1024	1568
f (%)[b]	45.7	36.2	34.0	38.3	na
$T1$[c]	0.67	1.33	1.65	0.26	4.57
(p-value)	(.67)	(.24)	(.13)	(.96)	(<.01)
$T2$	0.96	1.25	2.41	0.15	1.66
(p-value)	(.41)	(.29)	(.07)	(.92)	(.17)

Notes:

[a] A full set of sector-year dummies is included in all regressions. The reported r^2 is net of their contribution. Variables c, s and π refer to news in average variable cost,

sales and cash flow, estimated as residuals from a VAR(2) in logs of these variables, including year effects.

[b] f is the fraction of the covariance between investment revisions and R that is accounted for by the news in c, s and π,defined as $f = 1 - \sigma(yk^*, R^*)/\sigma(yk, R)$ where $yk^*$and R^* denote residuals in the regressions is Table 5.

[c] $T1$ tests that first and second lagged values of c, s and π are jointly zero. $T2$ tests that second lagged values are zero.

Table 7. Tests for Liquidity Constraints[a]

Investment Span

	$k=0$	$k=1$	$k=2$	$k=3$
$T1$: Zero Dividends	0.75	4.44[b]	0.01	1.08
	(.39)	(.04)	(.91)	(.30)
$T2$: Dividend Payout Groups	1.35	1.98	0.05	0.54
	(.25)	(.11)	(.98)	(.66)

Notes:

[a] The table entries are F-test statistics (probability values in parentheses). The tests are described in the text.

[b] The estimated response to news in cash flow is smaller for zero-dividend ($T1$) or low-dividend ($T2$) firms, contrary to the liquidity constraint hypothesis.

Appendix 1. Sector Composition of the Sample

Manufacturing	SIC Codes	No. of firms
Food & Tobacco	20-21	22
Textiles & Apparel	22-23	12
Lumber & Furniture	24-25	6
Paper & Printing	26-27	13
Chemicals & Drugs	28	25
Petroleum	13, 29	17
Stone, Clay &Glass	32	11
Iron & Steel	33	31
Fabricated Metal Products	34	7
Nonelectrical Machinery	35	37
Electrical Machinery	36	11
Transport Equipment	37	22
Scientific Instruments	38	6
Miscellaneous	30-31, 39	9
Nonmanufacturing		
Mining & Construction	10-16	8
Transportation Services	40-45	22
Communications & Public Utilities	48-49	33
Wholesale & Retail Trade	50-59	22
Finance & Insurance	60	4

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