Inventory Signals

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Among practitioners, inventory is often thought to be the root of all evil in operations management. The stock market hates it, the media abhors it, and managers have come to fear it. But high inventory levels can also be the result of strategic buying and high-availability strategies. The problem is that when the market sees lots of inventory, it cannot tell whether it is because of poor or smart operations. We hypothesize that inventory has a signaling role. In our model, publicly-traded firms use inventory levels to signal their operational competence to the market. There is a separating equilibrium that leads some firms to maintain inventory levels below what their capability could achieve. We offer this as one explanation why, for example, stock-outs are pervasive even among operationally competent firms. We provide empirical evidence for the assumptions behind this inventory signaling hypothesis: (1) the market cannot tell the difference between "good" and "bad" inventory; and (2) the counterfactual: the market punishes firms when it can tell that their inventory is bad, such as when they write off supplies. Consistent with these assumptions, we find that inventory levels do not explain firm value. And on average, stocks suffer an abnormal negative return of 7% in the month of announcing inventory write-offs.

Key words: inventory, signaling, perfect Bayesian equilibrium, write-off, event analysis

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1. Introduction

Roughly "a third of the consumers entering a store are looking for a specific item but fail to buy because they cannot find it." (Wharton at Work, 2002) The common explanation for this situation is poor operations management. Perhaps the store has weak forecasting capability, poor information systems, or long lead times (*e.g.*, Fisher and Raman (1996) and Fisher, et al. (2001)).

We offer an additional explanation: stock-outs might be due to managers' overly aggressive concern with inventory levels. A widely held belief among practitioners is that inventory is one of the clearest symptoms of poor operations management. "As far as I'm concerned, inventory is the root of all evil," says Victor Fung, Chairman of Li & Fung (Magretta 1998). Compounding this obsession with inventory is the asymmetry of information between publicly-traded firms and the capital market on what high levels of inventory really mean. They could certainly imply incompetence. But high inventory levels can also be the by-product of forward or bulk buying (e.g., Lal, et. al. 1996) or intentionally high service levels to reduce stock-outs (Arrow, Harris and Marschak, 1951). We can think of these strategic actions as investing in the future, to get a lower cost of goods or more loyal customers. The problem, it might be surmised, is that the stock market cannot tell whether a firm with high inventory levels is poorly managed or is investing in the future. Information on inventory levels is by comparison easier to get than information such as the benefits of forward buying, the lost opportunities due to stock-outs, or the magnitude of shrinkage and poor execution (e.g., Raman, et al. (2001)). Compared with other firms with similar financial statements, the market might assign a high-inventory but competent firm a lower valuation than it deserves. Facing such a situation, even a firm pursuing strategic buying or a high-availability strategy would rationally maintain a lower level of inventory than if such an asymmetry of information does not exist. In this way, we hypothesize that inventory has a ***signaling role***.

After a literature review in section 1, we formalize the intuition of the above argument in section 2. In section 3, we provide empirical evidence for two observable assumptions of our inventory signaling hypothesis: (1) that the market cannot tell the difference between "good" and "bad" inventory and, (2) that it punishes firms when their inventory that is obviously bad – *i.e.*, when it is written off. For the first, we use a panel dataset of firms drawn from COMPUSTAT and CRSP. Using several estimation methods, including fixed-effects and Heckman corrections for selection bias, and various measures of valuation such as Q, we find that the market offers statistically the same valuation to firms of varying inventory levels, controlling for other relevant variables. For the second, we cull from First Call a dataset of 61 announcements of inventory write-offs that have no confounding informational effects. Using event analyses based on market models and Fama-French factors, we find that the market punishes firms with inventory write-offs by depressing their stock returns by about 7% in the month of the announcement.

We qualify the signaling hypothesis in several ways. First, like all hypotheses, it can only be supported by non-falsification rather than proven with definitive evidence. Second, the hypothesis does not assert that stock-outs by competent firms must be due to inventory signaling. Rather, it says that all else being equal, lack of transparency on firms' strategies would lead firms to stock below their competence level. More provocatively, it predicts that competent firms' inventory and service levels would rise if firms' strategies become more transparent through say, policy reform.

2. The Signaling Role of Inventory

The modeling of asymmetric information in operations management has an early beginning, starting with work on decomposition schemes for multi-echelon stochastic inventory systems (Clark and Scarf, 1960). The emphasis in this stream of research is on designing optimal incentive systems among agents in a supply chain (see, for example, Cachon and Zipkin (1999), the review in Tsay, et al. (1999), and the special issue in Chen and Zenios (2005)). The closest works related to the model described in this paper are those of Ackoff (1967) and Porteus and Whang (1991). They highlight the conflict of incentives between a marketing department, which is keen to use higher inventory levels to avoid stock-outs, and a purchasing department, which is keen to have lower inventory levels to keep holding costs down. The latter paper also develops an internal futures market as an incentive-compatible solution to the problem. Others, beginning with Monahan (1984), work out pricing discounts that can induce purchasing managers to order quantities that are more optimal. These papers do not analyze the signaling role of inventory for publicly-traded firms, the subject of our paper.

In the economics literature, the work on costly signals begins with Ross (1973) and Spence (1973). The analysis in this paper is more closely associated with several themes in corporate finance. For example, it is along the same lines that Myers (1977) first show that information asymmetry between insiders and market leads to debt overhang, resulting in underinvestment of good projects (see also the models by Ross (1977) and Leland and Pyke (1977)). Indeed, the model here can be viewed as a re-interpretation of the class of models on managerial myopia and career concerns, such as those in Holmstrom (1999b) and Holmstrom and Ricart I Costa (1986) for labor markets, Fudenberg and Tirole (1986) in predatory pricing, and Stein (1988) and Stein (1989) in corporate finance. In these papers, the key idea is that firms are short-sighted, trading off efficient long-term investments for inefficient short-term benefits. They might do so for various reasons, such as the short-term nature of managerial compensation coupled with the opaqueness of information available to capital markets.

These initial "myopia models" spawn a very large literature, both in theory and empirics, ranging from banking, managerial incentives, product-market competition, capital structure, accounting, and marketing – examples of more recent work are those by Chemmanur and Ravid (1999), Prendergast (1999), Rotemberg and Scharfstein (1990), Fluck (1998), Srivastava, et al. (1998), Darrough and Rangan (2005). None, however, have considered the operations management setting. From a theoretical perspective, it seems natural to posit an inventory signaling hypothesis that argues for a signaling role of inventory.

In this paper, we are interested in empirically testing the basic assumptions of the hypothesis. As mentioned, these are: (1) whether the market can tell if high inventory in a firm is due to poor versus smart operations, and (2) when the market *is* able to tell the difference, whether the market punishes the firm. The hypothesis' assumptions rely on the answers to the first question to be "no" and the second to be "yes." The answers are not intuitively obvious. For example, it is plausible that information about inventory can be obtained at a sufficiently low cost - *e.g.*, by analysts plowing the aisles of supermarkets. With such information, the market *can* then tell whether high inventory is the result of poor operations or of smart strategy. Much of the analyst industry is predicated on this proposition. As an example, Raman, et al. (2005) report that Berman Capital purports to do just that. Much of the literature in finance, however, cast doubt on such a proposition (e.g., Treynor and Mazuy (1966), Fama (1970)). However, we acknowledge recent studies, such as Bollen and Busse (2001), that show that money managers have some ability to time the market. Interestingly, these same authors later show that such superior ability is short-lived (Bollen and Busse, 2004). Nevertheless, Gaur, et al. (1999) provide evidence that inventory levels might offer some explanatory power in explaining stock returns, but their study is on only the retail industry. Clearly, it is unsettled whether the market in general, and analysts in particular, can discern the value of firms based on public information about inventory and other aspects of operations strategy and management.

The second assumption, that the market punishes firms when they write off inventory, also does not have a consensus in the literature. There is a plausible alternative story that the market reacts *positively* to inventory write-offs. This might be because write-offs are seen as a signal that firms have put the worst behind them (the "favorable resolution" story rather than the "bad news" one, as framed by Elliott and Shaw (1988)), or write-offs are made in reaction to changes in fundamental conditions (*e.g.*, Francis, et al. (1996)). Either way, Elliott and Shaw (1988) note that "the financial press frequently treats these write-offs as though they are viewed favorably by the securities market.." Academic research is more guarded, since it is the surprise element, not the mere event of a write-off, which would be the logical driver of market reaction. Much of the accounting literature treats write-offs in aggregate terms, in the form of "big baths." In these cases, the documented market reaction is invariably negative. Two studies are particularly noteworthy. The first, by Francis, et al. (1996), documents market reaction to inventory write-offs. They conduct an event analysis based on write-off announcements reported in *PR Newswire* between 1989 and 1992. Although inventory write-offs are not the focus of the paper, they do report a -31.7% change in excess return over days -1 and 0, for the coefficient on write-off / assets dollar ratio. For our purpose, however, their result is subject to two biases. First, the sample period pre-dates SFAS No. 12, the accounting rule established March 1995 that specifies more stringent criteria for write-offs. Although it might be argued that the rule is targeted at long-lived assets, to the extent that discretion is introduced into the process, the test is a joint one, for market reaction and the write-off decision. Second, the analysis pre-dates recent innovations in event analysis, such as the use of Fama-French factors and industry controls. Therefore, it seems prudent to check the empirics of our model's assumptions.

The second, by Hendricks and Singhal (2003; 2005; 2005), looks at, among other things, the impact of announcements of production and shipping delays on firms' stock market returns. They classify these delays by cause (*e.g.,* customer-induced) and consequences (*e.g.,* quality problems). They find that returns drop by an order of 10% in the days -1 and 0 event period. Their study is therefore related to our study in that such delays could be due to underage in inventory. Since the focus of their study is not on inventory, none of their classifications of cause or consequence is specific to inventory levels or quality. Another difference is in methodology. In our study, we control for potential confounding informational effects in announcements, such as simultaneous announcements of earnings forecasts.

3. Model

We describe a model along the lines of the "myopia models" described earlier. There is no discounting over time and all agents are risk-neutral. We assume that the firm's managers and shareholders are aligned in interests and incentives. We discuss such agency issues in the conclusion. While the model is intended to capture the signaling role of inventory, it is general enough to be applicable to other operational signals.

In our model, there are two types of firms: competent (which we label *C*) and incompetent (*N*). It is common knowledge among firms and the market that a fraction p of the firm population is competent. A firm can take strategies with two dimensions. One dimension, observed by the market, is inventory level: high, medium, or low. The other dimension, unobserved by the market, is stock availability: also one of high, medium, or low. Figure 1 shows these strategic options. Competent firms have the freedom to adopt strategies along the diagonal, which can be interpreted as a strategic possibility frontier. This idea is reminiscent of the fit between functional versus innovative products and physically-efficient versus market-responsive supply chains, described by Fisher (1997). Incompetent firms are limited to the bottom left two cells. The top right cells beyond the strategic possibility frontier are infeasible: it is assumed not possible to implement say, high-availability with a lower level of inventory than even competent firms can. The left middle cell strategy of medium-availability with high-inventory is suboptimal for competent firms and assumed to be infeasible for incompetent ones[2].

If both availability and inventory dimensions of strategies are transparent to the market, we assume the market will assign competent firms the correct value of x_C and incompetent firms x_N, where $x_C > x_N$. We consider the situation in which the market cannot observe availability and analyze the case when it sees either high or medium levels of inventory. The case of observing low inventory level is uninteresting, since the market can accurately guess that firms are competent and assign them the correct value. We return to this later. The goal of our analysis is capture the *cost* and *benefits* of firms' deciding whether to take high or medium inventory strategies, in the face of a market that cannot tell competent firms from incompetent ones.

To capture *costs*, we assume that it costs firms to move from high to medium inventory levels. Specifically, it costs competent firms r_C and incompetent ones r_N , so that at medium inventory levels, the true value of firms are reduced to $(1 - r_C)x_C$ and $(1 - r_N)x_N$ respectively. For competent firms, this cost can also be

[2] It could be argued that we could assign the left-middle box to incompetent firms, but it turns out that the analysis is unchanged. We use our assumption to simplify the exposition.

interpreted as the cost of pursuing suboptimal "stuck in the middle" strategies (e.g., Porter (1980)). In Figure 1, it is a sounder strategic position to be in the top-left cell then the middle-center. In a departure from standard signaling models[3], we do not need to assume that $r_C < r_N$: it is not necessarily more costly for incompetent firms to reduce inventory. To reduce inventory, incompetent firms might have to incur more effort and money, but competent firms might have sacrifice more future profits if they do not take advantage of forward-buying or lose loyal customers because of frequent stock-outs.

To see the *benefits* of firms reducing inventory levels from high to medium, we return to the assumption that the market observes only inventory levels and not availability. When the market sees a high-inventory firm, it imputes a simple valuation based on *ex ante* probabilities:

$$p\, x_C + (1 - p)\, x_N\, .$$

Competent firms will see that their valuation is unreasonably low, since their true value is a higher x_C. Therefore, competent firms might reduce inventory to medium, to differentiate themselves from incompetent ones. Incompetent firms, facing this, have the incentive to mimic competent ones by lowering to medium level too to gain a higher valuation. We now incorporate both costs and benefits in a model of signaling to see who will do what. There are three stages.

In stage one, a firm observes its type: competent or incompetent. One way to think about starting positions is that the firm has a newly-appointed management team and is now poised to think what it should do. Another way to interpret this set up is that the competing landscape is always changing, and at stage one, this is where the firm finds itself.[4]

In stage two, each type of firm decides whether it should signal (*i.e.,* with medium inventory) or not (*i.e.,* stay with high inventory). Although the model rules out methods of signaling other than through inventory levels, it does not mean that other signals, such as investing in research or paying bonuses with stock rather than cash, are useful. It does mean that signaling through inventory is relevant at the margin Stein (1988).

In stage three, the market observes the level of inventory of a firm. The market then puts a premium m on lower (medium, in our case) inventory levels. This can be interpreted in several ways, all around the theme of patience of capital. A large m represents an impatient capital market, egging the firm onto signaling by

[3] The model described by Stein (1988) also departs from standard signaling models, but in his model, both types of firms have the same marginal cost of signaling. He makes this assumption because he assumes signals are small.

[4] In the economics literature, this is the familiar overlapping generations set-up, such as that in Kreps (1990).

reducing inventory in the short-term at the expense of longer term benefit. One practical interpretation of m is that it is the weight existing shareholders place on short-term observable performance. High inventory levels incurred through a high-availability strategy, even if they might lead to more loyal customers and better performance in the future, lead to undervaluation. This interpretation is related to the career concern models, although the latter are in the different context of managers rather than firms. As an example, Holmstrom and Ricart I Costa (1986) show that when managers worry about developing and protecting their reputation, they signal using short-term observables at the expense of longer term performance. Similarly, Stein (1989) shows how such short-term behavior can arise when managers place a premium on today's stock price that is based on expected value of noisy earning streams.

There can be other interpretations of m , showing the pervasiveness of the phenomenon: (1) the firm might need to raise funding in the stock market, so that a lower inventory level can provide the firm with a better valuation in such an event (*e.g.,* Grinblatt and Hwang (1989)), (2) managers in the firm face the probability m of being replaced if high inventory is observed, (3) *ceteris paribus*, the market views other information about lower inventory firms more favorably, with an m bias, (4) managers in the firm need to periodically sell off their shares in the firm, so they have to ensure that the firm is never undervalued, and (5) buyout raiders might take over an competent firm that has high inventory (*e.g.*, Stein (1988)); shareholders of the firm are forced to tender their shares for an undervalued price. Given these myriad interpretations, we summarize m as either what the market wants or the weight firms place on having lower inventory.

There can also be a probabilistic interpretation of m, with benefits that have a cumulative distribution function $F(v)$ and costs at c. That is, $m = 1 - F(c)$. In the takeover example of Stein (1988), for example, raiders incur a cost c of checking out the firm and if they were to takeover the firm and turn it around, the benefits v come with distribution $F(v)$. Therefore, the probability that v exceeds c is $1 - F(c)$, which is our m. In a more generic example, c might is the cost of diagnosing what is happening. For example, this could be interpreted as Berman Capital's effort needed to investigate the firm's inventory level, "patrolling the malls" and aisles (Alban 2004). Some elements of c could be determined by public policy. For example, the transparency of inventory information set by regulators and accounting standards can determine how much effort is needed to uncover the details. Laws for or against firing management or takeovers can affect c. To simplify our analysis, we skip F, v, and c and use the deterministic weight m.

We now describe the perfect Bayesian equilibria (PBE). Under PBE's, firms choose their optimal inventory level given the market's beliefs, which are in turn fulfilled by the equilibrium path. We also want these equilibria to satisfy the Cho and Kreps (1987) intuitive criterion off the equilibrium path. We adapt the mechanics in the myopia models, especially Stein (1988), to show the following.[5]

Proposition 1 – There exist a separating PBE that satisfies Cho-Kreps, for some parameter values.

To show proposition 1, we start with the observation that in a PBE in which competent firms always signal, the market has separating beliefs so that its Bayesian updating is as follows: (1) if it observes a high level of inventory, it is sure the firm is incompetent, and (2) if it observes a medium level of inventory, it is sure that is the firm is competent. In the former case, the market values the firm simply as x_N. In the latter case, the market values the firm as $(1 - r_C).x_C$, because it is not fooled about the cost of signaling. This is the point made in signal jamming models such as those first studied by Holmstrom (1999a) and Fudenberg and Tirole (1986).

We now examine the firm's actions to fulfill these beliefs. If the competent firm signals, it gets a value of $(1 - r_C).x_C$ for sure. If it does not, it gets x_N. This x_N is a short-term (under-)valuation, with a weight m ; the firm puts weight $1 - m$ on its true value x_C. Given these, the competent firm signals when:

$$(1 - r_C).x_C \geq m.x_N + [1 - m].x_C , \quad \text{or}$$

$$m \geq r_C.x_C / [x_C - x_N]. \tag{1}$$

The above is an expression for the break-even value of m in a separating equilibrium, which we denote that as m_s. For $m \geq m_s$, the pressure to reduce inventory is so high that the firm becomes myopic, sacrificing the better longer-term strategy of high-availability-high-inventory for medium-availability-medium-inventory.

The incompetent firm does not signal when:

$$(1 - r_N).x_C \leq x_N .$$

We assume the cost of signaling r_N for incompetent firms is so high it is not worth their while.

Proposition 2 – There exist a pooling PBE that satisfies Cho-Kreps, for some parameter values.

There are two pooling equilibria, one in which both competent and incompetent firms signal and one in which both do not. The former is less reasonable since both lose without gaining anything – a sort of Prisoner's Dilemma. Specifically, both firms reduce inventory by some small amount so that their valuations are reduced by a small amount $\varepsilon < x_N$; the market's belief out-of-equilibrium path is to conclude that any

[5] The main difference from Stein (1988) in our model are: (1) we use a typing of firms, (2) which leads us to impose additional constraints on m due to having two firm types, and (3) we use different signaling costs for different firm types.

firm that has a high level of inventory is incompetent. This equilibrium is not eliminated by Cho-Kreps. Nevertheless, we focus on the more interesting latter equilibrium. Here, the market has the following Bayesian updating process: (1) if it observes a high level of inventory, it concludes that the firm has the *ex ante* probability of being competent, (2) otherwise, it concludes the firm is competent. The latter is the only out-of-equilibrium belief that can sustain a pooling equilibrium. Pooling is sustained if, for the competent firm:

$$(1 - r_C).x_C \le m.[p.x_C + (1 - p).x_N] + [1 - m]x_C\,, \quad \text{or}$$

$$m \le r_C.x_C \,/\, [(1 - p).(x_C - x_N)]. \qquad (2)$$

For the incompetent firm, pooling is sustained if:

$$(1 - r_N).x_C \le m.[p.x_C + (1 - p).x_N] + [1 - m]x_N\,, \quad \text{or}$$

$$m \le [r_N.x_C - (x_C - x_N)\,]/[p.(x_C - x_N)] \qquad (3)$$

Therefore, pooling happens when $m \le m_p$, where m_p is the minimum of the m for both types of firms. When the m in (2) is the binding minimum, it is easy to see that $m_p \ge m_s$. In the middle zone where $m_p \ge m \ge m_s$, the result is ambiguous, with both separating and pooling equilibria sustainable. This is similar to Stein (1988). When (3) is binding, there may be no overlap between $m \ge m_s$ and $m \le m_p$, so that there is no defined equilibrium. It can be shown that mixed strategies such that firms signal with a probability provide equilibria in this zone. Firms' choice of separating, pooling, or mixed equilibrium in these ambiguous zones might be path-dependent. One intriguing interpretation of this is that private or public policies have lingering effects.

The upshot of this analysis is that system failures, poor inventory planning, or misaligned incentives between buyer and supplier need not be present for stock-outs to be pervasive. Given the widespread managerial and media focus on the "evils" of high inventory, and the simultaneous unobservability (to the market) of firms' strategies and their implications for inventory, it is only rational for firms to maintain lower than optimal levels of inventory. This analysis also makes precise how the parameters would lead to different equilibria. For example:

- Weight on short-term valuation, m. During the take-over wave of the 1980s, for example, we expect that firms are more myopic and tend to signal their competence with lower inventory, even among competent firms pursuing high-availability strategies. At that time, short-term valuation can be used as currency for acquisitions or defense against takeovers.
- Proportion of firms that are competent, p. In situations where most firms are incompetent, p tends to zero, m_p tends to m_s, and competent firms would be more likely to signal. An example of this might be

the furniture retail industry before consolidation, where most players tend to be subscale. In this case, the theory predicts that even competent firms have the incentive to stock less.

- Ability to reduce inventory, r_C and r_N. In a market where competent firms are much more capable of reducing inventory (say r_C tends to zero and r_N is small), separating equilibrium is predicted. As a hypothesis, we surmise that if Wal-mart is considerably more capable of managing inventory than its competitors, then a Wal-mart store that is otherwise the same as a competitor would tend to stock less.
- Ratio of valuation on incompetent firms to competent ones, x_N/x_C. As x_N/x_C tends to one (the two valuations are more similar), m_p and m_s tend to be high, and the theory predicts no signaling. This is what we might expect.

The analysis suggests that accounting standards that merely improve the transparency of inventory levels is a good first step, but what is also important is information on firms' operational strategy, such as availability levels and forward-buying.

4. Empirical Tests of Assumptions

We test the two assumptions of the model: (1) the market cannot use inventory levels to properly value firms and (2) when it can detect inventory as bad, it penalizes firms.

4.1 Valuation and Inventory

To test whether inventory information can explain stock valuation, we use the following specification:

$$VALUATION_{ft} = \beta_0 + \beta_1.INVENTORY_{ft} + \boldsymbol{X_f}.\boldsymbol{\beta_f} + \boldsymbol{W_{ft}}\boldsymbol{\gamma_{ft}} + \varepsilon_{ft} \,, \qquad (4)$$

where $VALUATION_{ft}$ is a suitable measure of the value of firm f at time t, $INVENTORY_{ft}$ is a suitably scaled level of inventory (and for robustness, is measured using inventory of various types, such as work-in-progress, finished goods), $\boldsymbol{X_f}$ are unobserved firm fixed effects, $\boldsymbol{W_{ft}}$ are relevant controls, and ε_{ft} are assumed to be independent, identically distributed innovations. Specifically for $\boldsymbol{W_{ft}}$, we follow the more recent practice for Q regressions, especially Gompers, et al. (2004), and include in it the log of assets and the log of firm age (Shin and Stulz, 2000), an indicator that is 1 if the firm is in the S&P 500 (Morck and Yang, 2001), and the governance index created by Gompers, et al. (2003). Because sales are potentially correlated with operations, we include log of net sales as a control too.

The data is obtained from a number of sources. From CRSP and COMPUSTAT, we obtain financial profiles of firms for years between 1950 and 2003. From IRRC, we obtain the governance index G. From

Professor French's website[6], we obtain the Fama-French industry classifications and their factors for returns regressions. We then link all firm-year observations from these sources, shown in Table 1, panel (a). While the number of observations appears large, we will not be able to use many of them because of the lack of data on a few crucial dimensions. The result is that we use an estimation sample, shown in panel (b). The sizes of the tests are still very significant. The observations not used provide sufficient information for a Heckman sample selection correction we undertake.

Table 2 reports the first and main measure of *VALUATION*, which is Tobin's Q. This has been used for firm valuation since Demsetz and Lehn (1985) and Morck, et al. (1988). We follow the method in Gompers, et al. (2003), and use the industry-adjusted median Q, which is the firm's Q minus the industry-mean, where we use the Fama and French (1997) 48 industries as classification.

Panel (a) shows the basic regressions, while panel (b) breaks the sample into quintiles by *INVENTORY*, since the setting in our theory is in situations with high inventory. Although not a major feature of our theory, it is more in conformance with the theory if the market offers firms with low inventory higher valuations. The intuition for this is that the market can tell that firms with low inventory are competent (please see figure 1), even if it cannot tell when it observes high or medium levels of inventory.

In panel (a), as a base case, Model (1) shows a straw man regression. This is a univariate pooled ordinary least squares regression of *VALUATION* on *INVENTORY*, in which the latter is measured using inventory turns (*i.e.*, inventory scaled by sales). While *INVENTORY* has some significance, the weakness of this specification is evident in the low adjusted *R* squared. In Model (2), we report the estimation of equation (4) with fixed effects on firms. Once we use this more reasonable specification, the significance on *INVENTORY* disappears. All the signs of the other coefficients replicate the usual results for Q regressions, such as those in Gompers, et al. (2003). The exception is the governance index, which is naturally insignificant here because we would not expect much within-firm heterogeneity on that.[7] In Model (3), we employ the Fama and Macbeth (1973) framework that is the *de facto* standard in the finance literature. The technique allows cross-sectional correlation while dealing with time-series correlations. We report only the second-stage means in the table. In Model (4), we deal with the potential problem of sample selection bias.

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[6] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[7] In a random-effects estimation, the governance index is significant at the 10% level. The *INVENTORY* variable continues to be insignificant. A Hausman test produces a $\chi^2(6)$ statistic of 57.11, so we reject the null that random effects are admissible, at the 0.000% significance level.

For example, looking at the difference between the two panels in Table 1, it might be argued that because the estimation sample is restricted to the 1990s and early 2000s, inventory levels might have been overwhelmed by noise in the technology bubble and accounting scandals. It can also be pointed out that the estimation sample is different in terms of cash cycles or asset intensity. To deal with possible bias, we employ a Heckman (1979) procedure using a probit selection model with the following covariates: year, age, market cap, receivables, payables, plant-property-and-equipment, and working capital.[8] The corrected estimation uses different measures of *INVENTORY* and has more control variables, as an example of the type of robustness tests used. Digressing on a note about robustness, we list here the different measures and controls that are also used for all previous models; the results are qualitatively the same and are not reported here:

1. *VALUATION*. Instead of Q, we also measure valuation with buy-and-hold returns[9] and the measures of performance described by Gaur, et al. (1999): year-on-year sales growth, operating margin, and return on equity.
2. *INVENTORY*. Instead of inventory turn on sales, we also use a finer breakdown, at the level of materials, work-in-progress, finished goods, and LIFO (last-in-first-out) reserves. As yet another alternative, we regress on inventory divided by assets, rather than sales.
3. Control variables: We include all the covariates in the Heckman selection model. In addition, we also have an indicator on whether the firm has undergone an acquisition or merger in the year prior to that of the observation, indicators for the identity of the auditor of the firm, indicators for different audit opinions[10], and inventory valuation methods.[11]
4. Econometric methods: Besides dealing with potential heteroscadasticity using Huber-White robust standard errors, we manage potential correlation with clustering and Fama-MacBeth techniques.

Returning to model (4), we report a regression with *INVENTORY* measured at a finer breakdown, with the additional control variables described above. We also cluster at the firm level to deal with serial

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[8] As usual, to reduce specification errors, we use logs for all but the year variable.

[9] The specifications on buy-and-hold return regressions follow those in Gompers, et al. (2003), in which we regress on *INVENTORY* as well as the usual Fama-French factors (*SML* and *HML*). The abnormal return is the alpha term of the regressions. Please see equation (5) later for details.

[10] Auditor opinions are classified into unaudited, unqualified, qualified, disclaimer or no opinion, unqualified with explanatory language, and adverse opinion.

[11] The inventory valuation methods are classified into: no inventory; first in, first out (FIFO); last in, first out (LIFO); "specific identification'; average cost; retail method; standard cost; current or replacement cost; not reported.

correlation. We once again obtain the result that *INVENTORY* does not explain *VALUATION*.

As pointed earlier, it might be counter-argued that our theory is one for high levels of inventory, and it would be stronger empirical support if we find that at low levels of inventory, inventory does explain valuation. In Table 2, Panel (b), we repeat the fixed effects estimation of Model (2) on quintiles of the sample, ordered by *INVENTORY*. As predicted, *INVENTORY* is not significant at high levels of inventory. Specifically, once inventory turn exceeds 0.115, we find that *INVENTORY* loses its explanatory power. Below this level, *INVENTORY* becomes increasingly significant as we go down the quintiles, and has the right (negative) signs. We also observe that each quintile regression is significant and has a small *p*-value.

4.2 Valuation and "Bad" Inventory

Our theory assumes that when the market sees high inventory, it does not know whether the inventory is good or bad and so it cannot properly value firms. For the theory to be robust, we test the counter-factual: if inventory is revealed to be bad, then the market will de-value the firm. We use an event analysis to test whether the market reacts negatively to announcements of inventory write-offs. This is a reasonable test because it provides some exogenous shock. However, like all tests of this nature, it is really a joint test of market efficiency (does the market react quickly?) and the null hypothesis of interest (does the market react negatively?). It is therefore, a one-sided test: if we find that the market reacts negatively, we can be persuaded that inventory write-offs are bad for firm valuation. However, if we do not find negative reaction, we cannot rule out the joint hypotheses.

We should also worry about factors that might confound the link between write-off and market reaction: (1) write-off decisions could be discretionary, (2) even if write-offs are not discretionary, decisions on the timing of announcements could be, and (3) even if both types of decisions are not discretionary, announcements of write-offs are often made at the same time as earnings announcements, so the reaction may be attributed to earnings information rather than write-offs.

Our datasets are constructed to deal with these issues. To deal with (1), we make use of one institutional detail, that write-off decisions after the March 1995 SFAS No. 12 have become less (but obviously not totally) discretionary. Therefore, we construct a sample after that date. Issue (2), fortunately, is not crucial to our study because the timing of announcements is orthogonal to our relationship of interest, between write-off and market reaction[12]. On (3), we construct a sample which we believe are rid of confounding news. We use the First Call dataset of earnings announcements, in which we first screen for announcements with footnotes on inventory write-offs.[13]

To eliminate the confounding impact of simultaneous earnings announcements, we restrict the sample to announcements in which the analyst consensus of expected earnings (within 90 days of announcement) is "near" the actual earnings. For robustness, we define "near" in different ways, as observations for which expected and actual earnings are within 5% of each other, and then within 0%, 1%, and 10%. These variations do not change the qualitative results and are not reported here. Table 3 shows the summary of the First Call sample using the baseline "within 5%" definition of "near". We see that CONSECO is unusual, being both a financial conglomerate (but classified as manufacturing in COMPUSTAT) and has a large $350M write-off. Table 4 shows the results of the event analysis, using Eventus (Cowan, 2003), with this observation. Estimations without it yield the same (unreported) results. In panel (a), we report the market-model analyses, which use a 90-day estimation window for the days analysis and a 7-month window for the months analyses. Both CRSP-indexed value- and equal-weighted models suggest the same behavior: there is significant negative reaction around the day of the announcement. As usual, there appears to be some news leakage before the day. The monthly analyses show the reaction clearly, with a -7.44% reaction in the month of the announcement. Panel (b) reports results from a Fama and French (1993) regression:

$$R_{jt} - R_{ft} = a_t + \beta_t(R_{mt} - R_{ft}) + s_t SMB_t + h_t HML_t + \varepsilon_{jt}\,, \tag{5}$$

where t is the time subscript, R_{jt} is the return for the jth stock, R_{ft} the risk-free return, R_{mt} the market return, SMB_t the small-medium-large factor, and HML_t the high-medium-low factor. This framework takes care of risk heterogeneity. The mean cumulative abnormal return is 7.73% in the month of the

[12] It is of course conceivable that late announcements might have some effect on the size of the market reaction to write-offs. Since we are primarily testing the direction of the reaction, this is not crucial. But even if we are interested in the size of the reaction, the fact that announcements cannot be delayed beyond a financial year suggests that the impact is probably not substantial. We should, however, bear in mind this factor when interpreting size effects.

[13] Specifically, we obtained all 114,139 footnotes with the word "Inventory," and after manual inspection of the footnotes, decide to screen for those with "Inventory" and one of the following words in the footnote: "reserve," adjacent "mark" and "down," "charge," "obsol" (for obsolete, obsolescence, etc.), "write" (for write-offs, write-downs, etc.), "loss." The items screened out are also manually inspected to ensure proper screening. The result is 1,145 footnotes. Although First Call says that the footnotes are issued with earnings announcements, we find that only some footnotes are linked to earnings announcements. It is unclear how the other footnotes are linked, so we restrict our sample to only the linked ones. We use different definitions of linking, including being on exactly the same dates and within 30 days of each other. There is qualitatively no difference in our results to these definitions. For the 30-day definition reported in this paper, there are 702 announcement observations. It is from these that we select the final sample which does not have confounding news on earnings, as described in the main text.

announcement, close to the result from the market-model.

Longer-term abnormal returns are outside the prediction of our theory, but we note that they are statistically indistinguishable from zero. This is consistent with the story that even inventory write-offs are noisy signals. The short-term negative reaction is an over-reaction and that given time, stock prices return to pre-announcement levels. We are more comfortable with the standard story that long-term returns are subject to many confounding intermediate effects (e.g., Mitchell and Stafford (2000)), although the first story would bolster our case that inventory signals are noisy.

5. Discussion and Conclusion

We have started with the observation that there is a general consensus among practitioners that inventory is root of many evils in operations management. The stock market hates inventory, the media abhors it, and managers detest it. Of course, inventory is not always bad. For example, it can be a by-product of a high-availability strategy or rational forward-buying. The problem is that market cannot tell what strategy firms are pursuing. It is difficult to measure service levels or communicate forward-buying implementation. We propose a model to analyze the implication of these observations. The model works out the signaling role of inventory. Under specified conditions, firms rationally want to lower their inventory levels below what optimal news-vendor solutions might suggest, so as to signal that they are operationally competent. The more it is perceived that high inventory levels are bad, and the more unobserved are firm strategies, the more this suboptimal cutback in inventory should happen.

The theory assumes that market cannot tell what high levels of inventory means, so at high levels, inventory levels cannot explain firm valuation. Our empirical results support this. Our model also assumes the counter-factual, that the market does react negatively to poor operations management, as when inventory is revealed to be bad. Our empirical results also support this.

We couch our finding as tentative evidence for the inventory signaling hypothesis. As with any hypothesis, it cannot be proven true but can be falsified, in the same way that say, the efficient market hypothesis in finance is supported not by being proven true but by voluminous failed attempts to falsify it.[14]

Our model has been worked out as if the firm is a monolithic, aligned entity, without agency problems between managers and shareholders. Suppose the managers are keen to not only increase share price for

[14] We acknowledge many recent substantive attempts to show that markets are inefficient – e.g., Shleifer (2000).

shareholders, but also their private benefits related to inventory. The latter benefits could come with higher levels of inventory (*.e.g.*, outright stealing of some of it, jobs for friends to handle the greater complexity, or a job that looks more important or secure with bigger warehouses). It could also come with lower levels of inventory (*e.g.,* an easier job with smaller warehouses). It does not appear that agency problems have a clear prediction of how they might modify our theory. This could be an interesting area for further research.

We see future work on several other fronts. One is more solid empirical evidence for the phenomenon of inventory signaling. A direct test is hard, because we need to benchmark inventory levels against what they "should have been." Another research direction is to look at other operational signals, such as receivables, payables, returns, or shrinkage. It might also be fruitful to see how signaling in the way described here might be applicable not with capital markets, but with others in the supply chain (e.g., Iyer, et al. (2005)). Finally, it is intriguing to examine the corporate governance and public policy issues associated with fixing the problems analyzed here, to improve overall welfare.

What is the implication of all this for management? Inventory has a signaling role primarily because of two factors: (1) the market cannot observe firms' operations strategies, and (2) capital markets are impatient and nervous about waiting for the possibility that the firm in question actually has competent management, and that high levels of inventory would pay back in the future in terms of say, more loyal customers (high-availability) or lower costs-of-good-sold (forward-buying). Fixing (1) might require making inventory accounting more transparent. The analysis suggests that another lever is in fixing (2). A logical guess is that high-availability operations are usually associated with (or should be sought by) patient, sophisticated investors. Perhaps this is why, among other reasons, many high-availability outfits, from the Ritz Carlton to Coutts (the private bank), are or have to be privately-held, at least for long periods of their history.[15] Our analysis also works out what all wise shareholders and other principals know, that obsessions with single dimensions of performance measures such as inventory often have insidious effects on incentives and optimization.

[15] As an example, the Ritz-Carlton was in private hands for much of its history since the late 1800's, from Edward Wyner and Gerlad Blakely to William Johnson. It was bought by Marriott International in 1995. Marriott, of course, is also a closely held firm (source: Ritz-Carlton corporate website).

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Figure 1 – A Model of Strategic Options and Firm Types (*C* = competent firm, *N* = incompetent).

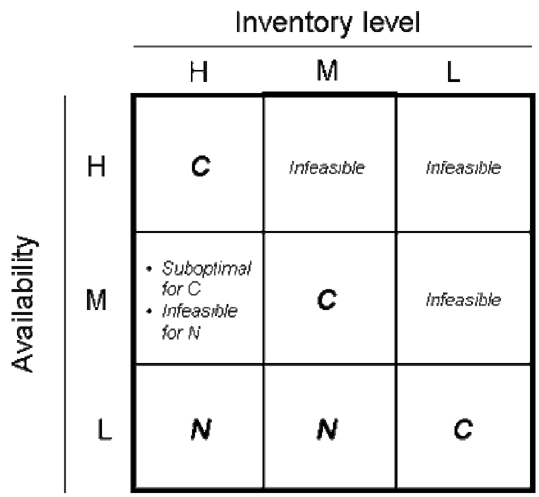

Table 1 – Summary Statistics of Sample for Valuation Analysis

(a) Full sample

Variable	Obs	Mean	Std. Dev.	Min	Max
Year	228,958	1987	12	1950	2003
Net sales ($M)	211,258	1,018	5,367	-204	257,157
Q	176,111	2.2	43.7	0.05	14,207
Op Income before depr ($M)	206,746	167	1,008	-5,743	61,188
Inventory - total ($M)	204,723	148	2,290	-3	372,998
Inventory – materials ($M)	111,537	24	139	0	6,457
Inventory – work in prog ($M)	105,172	21	188	-37	12,114
Inventory – finished goods ($M)	109,397	44	257	-8	14,298
Inventory – LIFO reserves ($M)	144,585	12	112	-139	7,700
Inventory total/net sales (turn)	201,726	0.19	3.98	-34.66	1,671.00
Inventory total over assets	204,677	0.16	0.17	-0.01	22.45
Age	228,958	10.4	9.6	1	54
Market cap ($M)	211,073	1,003	7,012	0	508,330
Receivables ($M)	204,167	707	9,209	0	912,604
Payables ($M)	193,751	609	8,458	0	643,556
Plant, property, equipment ($M)	192,607	85	540	-290	33,143
Working cap ($M)	181,879	89	618	-37,532	46,313
S&P 500	15,398	1	0	1	1
G index	7,128	9	3	1	18
Acquisitions	228,958	0.065	0.247	0	1

(b) Estimation sample (*i.e.*, with observations on all relevant variables)

Variable	Obs	Mean	Std. Dev.	Min	Max
Year	5973	1997	4	1990	2002
Net sales ($M)	5973	3,859	10,337	0	184,214
Q	5973	1.8	1.6	0.3	37.8
Op Income before depr ($M)	5896	734	2,651	-3,695	61,188
Inventory - total ($M)	5973	666	5,895	-	173,388
Inventory – materials ($M)	3470	73	260	-	6,457
Inventory – work in prog ($M)	3305	57	256	0	7,051
Inventory – finished goods ($M)	3501	139	416	-	7,319
Inventory – LIFO reserves ($M)	5275	28	162	-60	6,800
Inventory total/net sales (turn)	5973	0	1	-	31
Inventory total over assets	5973	0.12	0.14	0	0.91
Age	5973	22.9	14.2	1	53
Market cap ($M)	5973	5,317	19,838	1	476,116
Receivables ($M)	5895	857	9,003	-	414,886
Payables ($M)	5918	2,217	21,092	-	802,608
Plant, property, equipment ($M)	5876	285	1,064	(0)	33,143
Working cap ($M)	5403	269	1,223	-33,780	35,832
S&P 500	5973	0	0	-	1
G index	5973	9	3	1	18
Acquisitions	4444	92	779	-571	34,697

Table 2 – Valuation and Inventory.

(a) Estimations on all *INVENTORY* quintiles

Dependent variable: VALUATION, measured with median Q	(1) OLS	(2) Fixed effects	(3) Fama-Macbeth	(4) Heckman correction
Total inventory	.021 (.005)***	-.063 (.121)	-.086 (.057)	
Materials inventory				-.031 (.070)
Working capital inventory				-.024 (.721)
Finished goods inventory				-.587 (.373)
LIFO reserves				2.065 (1.414)
CONTROLS				
Log assets		-.683 (-.683)***	-.164 (.027)***	-1.440 (.086)***
Log firm age		-.262 (.086)***	-.069 (.030)***	.196 (.047)***
Log sales		.723 (.069)	.129 (.029)***	.215 (.058)
S&P 500		1.96 (.59)***	.377 (.055)***	.071 (.082)
G, governance index		-.00059 (.01730)	-.007 (.008)	-.014 (.059)
Log market cap				1.424 (.090)***
Log receivables				.011 (.057)
Log payables				-.154 (.049)***
Log working cap				-.082 (.032)**
Indicator for acquisition				.106 (.044)**
Indicator for year				Yes
Indicator for Inventory method				Yes
Indicator for auditor firm				Yes
Indicator for audit opinion				Yes
Constant	2.057 (.102)***	.535 (.312)*	.638 (.128)***	-1.081 (.606)*
N	169,446	5,973	5,973	6,040
Adj. R squared	.01%	6.26%		-
p-value	.0001	.0000		.0000

(b) Estimations on all INVENTORY quintiles using fixed effects model (2)

Quintile	1	2	3	4	5
INVENTORY level	0.00 to .013	.013 to .066	.066 to .115	.115 to .175	.175 to 30.7
Coefficient on *INVENTORY*	-56.9 (24.7)**	-8.16 (4.77)*	-5.27 (3.12)*	-2.75 (3.24)	.124 (.139)
Adj *R* squared	5.7%	1.0%	0.9%	2.0%	2.5%
p-value	.000	.074	.000	.000	.000

*** Significant at the 1% level, ** at 5%, * at 10%. Figures in brackets are standard errors.

Table 3 – Summary Statistics of Sample for Event Analysis (example first 42 of 61 firms, by firm name)

		EPS ($) ANNOUCEMENT					
	FIRM	ANNOUNCE DATE	ACTUAL	MEAN EST	MED EST	FOR PERIOD	FIRST CALL FOOTNOTE
1	A G C O CORP	3-Feb-00	-0.20	-0.20	-0.20	31-Dec-99	0.05 inv writedown
2	A M L I RESIDE	5-Feb-02	2.59	2.70	2.70	31-Dec-01	exc 0.08 charge fr inv
3	A M X CORP	19-Jan-99	0.16	0.16	0.16	31-Dec-98	0.14 inv writedown
4	A V X CORP NEW	10-Oct-01	0.02	0.02	0.02	30-Sep-01	$32.5M inv writedown
5	ADFLEX SOLUTIO	19-Jan-96	0.36	0.37	0.37	31-Dec-95	1.88 inv writedown
6	ADVANCED RADIO	10-Nov-98	-0.56	-0.58	-0.53	30-Sep-98	$2.7M inv writedown
7	ALBERTO CULVER	27-Jul-95	0.25	0.24	0.23	30-Jun-95	0.02 inv writedown
8	AMERICAN HOME	18-Oct-99	0.48	0.47	0.47	30-Sep-99	0.07 inv writedown
9	ASHLAND INC	25-Jan-99	0.62	0.60	0.65	31-Dec-98	0.76 inv writedown
10	AVIALL INC NEW	12-Feb-02	0.51	0.50	0.50	31-Dec-01	exc $8.9M net loss on inv, intan writedown
11	AVONDALE INDUS	28-Jan-99	2.23	2.18	2.18	31-Dec-98	exc 0.10 charge fr steel inv adjustment
12	B H A GROUP HO	20-Jul-99	0.12	0.12	0.11	30-Jun-99	0.04 inv writedown
13	BELLSOUTH CORP	20-Oct-99	0.51	0.50	0.50	30-Sep-99	Restated fr 0.51 down for inv writedown.
14	BERINGER WINE	28-Oct-99	0.42	0.41	0.41	30-Sep-99	0.04 inv writedown
15	BERINGER WINE	27-Apr-99	0.49	0.47	0.47	31-Mar-99	0.11 inv writedown
16	BROWN SHOE INC	27-Feb-02	1.61	1.62	1.62	31-Jan-02	exc 0.60 charge fr inv markdowns
17	CABLE DESIGN T	1-Oct-01	0.93	0.93	0.92	31-Jul-01	exc 0.04 charge fr bad debt and inv valuation
18	CAMTEK LTD	13-Nov-02	-0.05	-0.05	-0.05	30-Sep-02	0.07 inv writedown
19	CARAUSTAR INDU	12-Feb-96	0.51	0.51	0.50	31-Dec-95	$4.8M inv writedown
20	CELADON GROUP	27-Apr-98	0.24	0.24	0.24	31-Mar-98	0.04 inv writedown
21	CHASE INDUSTRI	12-Feb-99	0.22	0.22	0.22	31-Dec-98	0.14 inv writedown
22	COCA COLA CO	19-Jul-00	0.42	0.41	0.41	30-Jun-00	0.02 inv writedown
23	CONGOLEUM CORP	6-May-96	-0.10	-0.10	-0.10	31-Mar-96	0.01 inv writedown
24	CONSECO INC	23-Feb-00	3.23	3.36	3.20	31-Dec-99	$350M inv writedown
25	D D I CORP	29-Jan-02	0.41	0.42	0.41	31-Dec-01	exc $3.7M charge fr inv impairment
26	EON COMMUNICAT	29-Aug-02	-0.32	-0.32	-0.32	31-Jul-02	exc 0.07 charge for adj value of excess inv
27	EXAR CORP	22-Oct-02	0.04	0.04	0.04	30-Sep-02	$2.3M inv writedown
28	FALCON PRODUCT	3-Sep-98	0.25	0.26	0.26	31-Jul-98	0.31 inv writedown
29	FIRST HORIZON	6-Nov-02	0.07	0.07	0.06	30-Sep-02	$1.2M inv writedown
30	GENUINE PARTS	19-Feb-02	2.08	2.11	2.10	31-Dec-01	exc $17.4M charge fr inv exit
31	GOODYEAR TIRE	21-Oct-99	0.51	0.49	0.51	30-Sep-99	0.63 inv writedown
32	GUESS INC	8-Mar-01	-0.30	-0.30	-0.31	31-Dec-00	$5.7M inv writedown
33	GULFSTREAM AER	9-Feb-99	3.00	2.94	2.95	31-Dec-98	inc 4.5M charge fr inv setup, goodwill amorti
34	H M T TECHNOLO	14-Jan-99	0.03	0.03	0.03	31-Dec-98	0.04 inv writedown
35	ILLINOVA CORP	1-May-97	0.08	0.08	0.08	31-Mar-97	0.01 inv writedown
36	J D S UNIPHASE	24-Jan-02	-0.02	-0.02	-0.02	31-Dec-01	$80M inv writedown
37	KIMBERLY CLARK	22-Oct-98	0.63	0.62	0.62	30-Sep-98	0.13 inv writedown
38	L T X CORP	14-Feb-02	-0.26	-0.26	-0.26	31-Jan-02	$42.2M inv writedown
39	MCDONNELL DOUG	18-Jul-95	0.74	0.72	0.73	30-Jun-95	0.10 inv writedown
40	METRICOM INC	12-Feb-98	-0.95	-0.93	-0.93	31-Dec-97	0.26 inv writedown
41	MICROWAVE POWE	25-Jul-96	-0.05	-0.05	-0.05	30-Jun-96	0.06 inv writedown
42	MONACO COACH C	7-May-96	0.05	0.05	0.05	31-Mar-96	0.08 inv writedown

Table 4 – Results of Event Analyses

(a) Market-model

Days	N	Mean CAR[1]	Precision weighted CAAR[2]	t	Generalized sign Z[3]
			Value-weighted		
(-30,-2)	61	-6.25%	-5.43%	-2.348***	-1.861**
(-1,0)	61	-0.24%	-0.54%	-0.343	0.964
(+1,+30)	61	-6.03%	-7.52%	-2.228**	-1.348$
			Equal-weighted		
(-30,-2)	61	-3.80%	-2.47%	-1.416*	-1.01
(-1,0)	61	-0.08%	-0.23%	-0.109	0.529
(+1,+30)	61	-4.74%	-6.07%	-1.739**	-0.753

Months	N	Mean CAR	Precision weighted CAAR	t	Generalized sign Z
			Value-weighted		
(-6,-2)	60	-7.02%	-8.38%	-1.125	-0.945
(-1,0)	60	-7.44%	-8.94%	-1.885**	-1.462*
(+1,+6)	60	-0.10%	-0.11%	-0.015	0.606
			Equal-weighted		
(-6,-2)	60	-7.50%	-7.80%	-1.268	0.104
(-1,0)	60	-8.48%	-9.48%	-2.267**	-2.220**
(+1,+6)	60	-2.60%	-2.35%	-0.402	-0.154

(b) Fama-French factors

Days	Mean CAR	T
(-30,-2)	-3.99%	-1.384**
(-1,0)	0.24%	0.234
(+1,+30)	-4.82%	-1.677***

Months	Mean CAR	T
(-12,-2)	-15.62%	-2.184**
(-1,0)	-7.73%	-2.588***
(+1,+12)	6.57%	0.653

[1] CAR = cumulative abnormal return. It is the sum of the prediction error (see equation (2)) over the period concerned.

[2] CAAR = cumulative average abnormal return. For trading days from T_1 to T_2, this is $\frac{1}{N}\sum_{j=1}^{N}\sum_{t=T_1}^{T_2} a_{jt}$ where a_{jt} is the abnormal return for the jth stock at time t.

[3] The Generalized sign Z statistic tests the null that the fraction of positive returns is the same as in the estimation window; see Singh, et al. (1991).

*** Significant at the 1% level, ** at 5%, * at 10%.