Inventory Signals

Richard Lai

Harvard Business School

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How does operational competence translate into market value, when firms cannot credibly communicate their competence to the market? I consider the example of inventory and fill rates. When the market sees a high-inventory firm, it cannot tell whether the inventory is due to incompetence or to a strategy to enhance fill rate. Firms might decide to signal their competence to the market by carrying less inventory. I show conditions for separating and pooling perfect Bayesian equilibria. I also provide empirical evidence consistent with three sharp predictions of this theory that inventory has a signaling role. The theory could potentially provide a framework that describes one way in which a range of operational competences—such as investments to boost customer service or outsourcing to reduce costs—could translate to market value. Practically, it has implications for firms, such as how to strategically communicate to the market, reward managers, or even whether to go public and be subject to market pressures.

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1. Introduction

How does operational competence translate into market value for firms? This is a central question in operations management, tying operational decisions to financial impact.

If competence is fully transparent to the stock market, then it might be fairly valued. In reality, the market cannot observe many aspects of operational competence inside firms. At the same time, firms cannot credibly communicate their competence to the market. Therefore, the market infers firms' competence from observable proxies. This could be a rather general phenomenon. For example, the market might infer customer service levels from investments made in call centers, the quality of the R&D pipeline from R&D spending, or the risk profile from investments in risk management (*e.g.,* Kekre, et al.

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(2003) for check-processing). Or the quality of the purchasing function from the costs of inputs purchased. Or the value of outsourcing from the contract price. Knowing this, firms have incentives to manage these proxies to get the highest valuation, and knowing that, the market values these proxies differently than if firms do not manage them. What holds in equilibrium?

I describe equilibria in the setting of inventory and fill rates. When the stock market sees a high-inventory firm, it cannot tell whether the inventory is due to incompetence or a strategy to enhance fill rate. Competent firms decide whether to signal their competence to the market by lowering inventory levels, thus distinguishing themselves from incompetent firms who cannot lower inventory as easily. So for these competent firms, signaling gets better valuation in the short term, but is costly in the long term if the first-best strategy is to maintain higher fill rates and higher inventory. The decision to signal hinges on this balance between short-term benefits and long-term costs. I describe conditions for which competent firms signal, so that a separating perfect Bayesian equilibrium (PBE) obtains, and when they do not, so that a pooling PBE is observed. In short, this is a theory that inventory has a signaling role.

I also report empirical evidence for this theory using a panel dataset of firms drawn from the merged CRSP-COMPUSTAT tapes, IRRC, I/B/E/S, ExecuComp, and First Call. Specifically, I test three predictions of the theory, regarding the existence of an incentive to signal (high inventory firms do not get better valuations), short-termism (firms care about short-term valuation), and information asymmetry (firms cannot credibly communicate their competence to the stock market).

To test the first—an incentive to signal—I run fixed effects regressions of valuation on inventory. If inventory and valuation are positively correlated, then that falsifies the prediction that high inventory firms suffer. But I find that it is low-inventory firms that get better valuations, consistent with an incentive to signal. The difference is economically significant. For example, the difference in Tobin's q between the lowest and highest inventory firms is 0.94, which is on the same order as the q mean (0.40) and standard deviation (1.65). I handle endogeneity issues with the use of a variety of lag structures. The estimations are also robust to different measures of valuation (*e.g.,* buy-and-hold returns) and inventory (*e.g.,* total vs. finished goods inventory, scaling). Valuation is also estimated with a number of controls, such as those variables consistent with the story that the market is simply assigning higher valuations to better firms, which tend to carry less inventory. Of course, the result could still be explained by stories other than signaling. One example is that the market could be inefficient, over-valuing low-inventory firms. However, none of the alternative explanations involve short-termism and information asymmetry, so tests of these can be used to rule out the non-signaling stories.

To test short-termism, I investigate the model's prediction that shorter-term industries have more separation. In one test of this mechanism, I check if industries in which the average executive has more stock and options holdings (interpreted as more short-term) are correlated with negative sensitivity of valuation to inventory (more separation). The result holds up. It is also economically significant. One standard deviation in stock holdings changes the mean sensitivity by 54% of its standard error.

To test information asymmetry, I investigate the model's prediction that when asymmetry is suddenly reduced, such as when firms write off bad inventory, they suffer a drop in valuation more than what the size of the write-off itself implies. In other words, a write-off announcement has informational content about the competence of the firm. The model further predicts that drops in valuation should be larger in industries with more pooling. With more pooling, more competent firms get mixed up with incompetent ones, so that the pooled valuation might be very high. The valuation of a firm that reveals itself to be incompetent can therefore fall a lot from this high pooled valuation. I report empirical evidence consistent with these, using event analyses that take care of confounding informational effects of write-off announcements, possible leakage before the announcements, the fact that firms tend to bunch up bad announcements, *etc*. For example, I find that post-announcement valuations are only 78% of those predicted without signaling.

To sum up, only the signaling story appears to be consistent with the results of all three tests.

This paper contributes to the literature that ties operational decisions to stock market performance. One stream of the literature studies market reaction to announcements. For example, Klassen and Mclaughlin (1996) report that the market reacts positively to announcements of environmental management awards. Corbett and De Groote (2000) find likewise, for ISO 9000 certification. Hendricks and Singhal (2005a) look at reactions to supply chain disruptions and Hendricks and Singhal (1997) at awards for total quality management.

Another stream of research takes a different empirical approach, using panel datasets to look at correlations between operations and valuation. For example, Chen, et al. (2005) find that lower-inventory firms have better stock returns, except those with the lowest inventory levels. Although Gaur, et al. (2005a) correlate inventory with gross margin rather than valuation, to the extent that gross margin is correlated with valuation, it is also in that stream of research.

This paper adds to both these streams of research in that it articulates a richer theory of one possible interaction between operations and valuation. It also places the interaction mechanism (signaling) on micro-economic foundations. While the setting in this paper is on inventory, it would be intriguing to see the extent to which the story here could also describe how a vast range of operational competences—such as customer service, purchasing, outsourcing, or research capabilities—translates to market value. Practically, the signaling story has implications for firms, such as how to strategically communicate to the market, reward managers, or even whether to go public and be subject to market pressures.

2. The Signaling Role of Inventory—A Simple Model

The model I describe builds on general work in signaling that begins with Ross (1973) and Spence

(1973). More specifically, my model is associated with those in corporate finance, especially models of managerial myopia and career concerns. Examples of these are Holmstrom and Ricart I Costa (1986) for labor markets, Fudenberg and Tirole (1986) in predatory pricing, and Stein (1988) and Stein (1989) in acquisitions. These pioneering "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), and Srivastava, et al. (1998). None, however, has considered the operations management setting.

In operations management, the focus is on conflicts of incentives. For example, a 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 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. Still other examples include Deng and Elmaghraby (2003), who study how buyers can use tournaments in sourcing, when they can observe only noisy signals about suppliers. Li, et al. (2005) also consider the case of information asymmetry along a supply chain. They study how asymmetry is correlated with different types of supply chain contracts. Zlobin, et al. (2003) look at information asymmetry at the retail level, and consider how moral hazard affects the financing of dental care. While all these papers study aspects of incentives and information asymmetry, they do not analyze the signaling role of inventory for publicly-traded firms, the subject of this paper.

I describe the model in the setting of inventory and fill rates, adapted from Stein (1988). Among practitioners, inventory is often considered a central issue in operations management. It "plays a key role in the logistical behavior of virtually all manufacturing systems" (Hopp and Spearman (2000), pg. 48). Victor Fung, Chairman of Li & Fung, remarks that "as far as I'm concerned, inventory is the root of all evil." (Magretta 1998) Managers also treat inventory as an important signal to the stock market and a yardstick for comparison with other firms. For example, Steve Jobs declares in a 1999 analyst briefing that "last quarter, we ended with less than a day of inventory—15 hours. As a matter of fact, we've beat Dell now for the last four quarters." (Sheffi (2005), pg. 226). These points—that inventory is an important managerial concern, especially in view of managing it with a view to the stock market—are also reinforced in direct conversations with retail executives (CORE (2005), CORE (2006)).

As this is primarily an empirical paper, I shall use graphical and simple algebraic descriptions of the model. I also make some simplifying assumptions, such as having just two types of firms. Readers interested in a formal derivation are referred to an earlier version of this paper (Lai (2005)).

Figure 1, panel (a), depicts the model. There is no discounting over time. All agents are risk-neutral. There are two types of firms: competent (which I label *C*) and incompetent (*N*). Firms adopt inventory positions (horizontal axis) to achieve desired fill rates (vertical axis). I do not mean that fulfilling the optimal fill rate is the only role of inventory. Other roles could be to smooth production or to take advantage of forward buying (see Arrow, et al. (1951)). I interpret achieving the fill rate as a proxy for what might be a collection of reasons for inventory. The model only needs the long-term optimum of this collection (fill rate here) to be imperfectly observable to the market.

In panel (a), both *C* and *N* firms adopt positions along the curves, which can be interpreted as strategic possibility frontiers. *C* firms are able to achieve the same fill rate with less inventory. In addition, *N* firms are defined so that they cannot go below a certain inventory level (the *x*-intercept in the figure). Along the frontiers, firms have exogenous long-term optimal positions. These positions, interpreted as first-best, might arise from competitive positioning (*e.g.,* Porter (1980)) or resource endowments (*e.g.,* Penrose (1959)). Moving away from these first-best positions incur costs. This is also one of the points of Fisher (1997), that there needs to be a fit between product type (functional versus innovative) and supply chain configuration (physically-efficient versus market-responsive). Deviating from first-best positions further incurs a loss of complementarity with other parts of the firms (*e.g.,* Milgrom and Roberts (1995)).

The fair valuations of *C* and *N* firms are x_C and x_N, with $x_C > x_N$. In the long term, an efficient market will assign to these firms these fair valuations. However, in the short term, the market has to estimate valuations, since the market cannot observe whether a firm is on the upper frontier (*C* firm) or lower (*N* firm), but it can see only the inventory position on the horizontal axis. Therefore, the stock market has to deduce the valuation for observable high-inventory versus low-inventory firms. Given this, *C* firms whose first-best positions are high-inventory-high-fill rate (to the right of the vertical dashed line) worry about the stock market mistaking them for *N* firms. Therefore, they might consider shifting southwest along the frontier, from their first-best position (high-inventory-high fill rate) to one of low-inventory-low-fill rate. Such deviations from first-best (signaling) has an exogenous cost, denoted r_C, and reduces these *C* firms' true long-term valuations x_C. Firms use this calculus, balancing short-term benefits and long-term costs, to decide if they should deviate (*i.e.,* signal).

In settings outside of inventory, signaling may involve *not* doing something, and the idea is similar: balancing short-term costs against long-term benefits. An example is not investing in projects that require short-term outlay to obtain long-term benefits. The outlay is immediately understood by the market while the benefits may not be so. Boyer (1999) reports that investments in administrative, design, and manufacturing technologies enhance financial performance only after a lag. Sterman, et al. (1997) find that total quality management programs incur short-term costs for productivity increases and lower costs that come only in the long term. Bharadwaj, et al. (1999) and Bresnahan, et al. (2002) document that information technology investments provide benefits with a lag.

In the model, the tradeoff between the short- and long-term is captured in a premium m that firms place on their short-term valuation. But why does short-termism exist (*i.e.,* m>0) and what determines its degree (*i.e.,* the size of m)? Short-termism might arise, for example, because firms' managers are concerned about their short-term reputation in the job market (*e.g.*, Holmstrom and Ricart I Costa (1986)). Such firms signal using short-term observables such as lean inventory or reduced investments in customer service, at the expense of longer-term performance. Firms might also need to raise funding in the stock market, so a lower inventory levels provide them with better valuation for this short-term purpose (*e.g.,* Grinblatt and Titman (1989)). Stein (1988) and Stein (1989) offer other reasons. Managers might want to sell off their shares in their firms in the near term, so they have to ensure that their firms are not under-valued during the period. Managers fear losing their jobs if buyout raiders take over their firms, which is likely if the firms have high inventory and are under-valued; shareholders of the firms might also be forced to tender their shares for the under-valued price.[2]

It is common knowledge among firms and the market that a fraction f of the high-inventory firms is competent. I also assume that firms' managers and shareholders are aligned in interests and incentives. I discuss agency issues in the conclusion. Signals are sent by firms to only the stock market. The story can be generalized to the extent that other capital markets rely on firms' equity valuations—*e.g.,* the debt market uses equity valuation in collateral assessments. Although the model rules out methods of signaling other than through inventory levels, I do not mean that other signals are not useful. It does mean that signaling through inventory is "relevant at the margin" (Stein (1988), pg. 65).

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[2] The parameter m can also be interpreted probabilistically. In the takeover example of Stein (1988), for example, raiders incur some cost c of checking out target firms and if they were to takeover these firms and turn them around, the benefits v come with distribution $F(v)$. Therefore, the probability that v exceeds c is 1 - $F(c)$, which is my m. As another example, much of the analyst industry is predicated on the proposition that analysts can get better information, such as fill rates, and do a better job of assessing the true value of firms. Raman, et al. (2005) report that Berman Capital purports to do just that. In general, c could be interpreted as the cost for reducing the degree of information asymmetry. The cost c could also be interpreted as a public policy parameter. For example, regulators and accounting standards set a low c when they require more disclosure of information. Laws for or against firing management or takeovers can affect c. To simplify our analysis, and without loss of generality (see Stein (1988), for example), I skip F, v, and c and use the deterministic weight m. Please see Lai (2005) for details.

I now describe the perfect Bayesian equilibria (PBE). Under PBE's, firms choose their inventory level given the market's beliefs, which are in turn fulfilled by the equilibrium path. The PBE's should satisfy the intuitive criterion of Cho and Kreps (1987) off the equilibrium path.

Proposition 1 – A separating PBE satisfying Cho-Kreps exists, for some parameter values.

Figure 1, panel (b), illustrates this. Suppose it is common knowledge that the proportion of *C* firms that might separate is *g*. In the figure, this is the portion of *C* firms to the right of the vertical divider. To show proposition 1, I start with the observation that in a PBE in which *C* firms always signal, the market has beliefs with Bayesian updating as follows: (1) if it observes some firms with high levels of inventory, it is sure these are *N* firms, and (2) if it observes firms have low levels, it is sure that these are *C* firms. In the former case, the market values the firms simply as x_N. In the latter case, the market values the firms according to the proportion of *C* firms that signal, $(1 - g).x_C + g.(1 - r_C)x_C$. The market values high-inventory firms who separate at $(1 - r_C).x_C$, because it is not fooled about the cost of signaling. This follows the logic in signal jamming models such as those in Fudenberg and Tirole (1986) and Holmstrom (1999).

How do firms' actions fulfill these beliefs? By definition, *N* firms cannot signal. If a *C* firm signals, its true long-term value declines to $(1 - r_C).x_C$. In the short term, it gets pooled with *C* firms that do not need to signal. It puts weight *m* on this short-term (over-) valuation and (1-*m*) on its long-term valuation. If it does not signal, it gets x_C in the long term and x_N in the short-term. Given these, *C* firms that face signaling decisions signal when:

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

$$(1) \qquad m \geq r_C.x_C\,/\,[(1 - g).r_C.x_C + x_C - x_N]\,.$$

The above is an expression for the break-even value of *m* in a separating PBE, which I denote as m_s. For $m > m_s$, the pressure to reduce inventory is so high that such *C* firms become myopic, so that their second-best points are at a lower fill rate than their first-best positions.

An interesting result from the above is that, in the short-term, *C* firms with low fill rates (left of the vertical in panel (b)) get mixed up with the other C firms that separate. To the extent that this leads to inefficiencies among the former group of *C* firms, the welfare effect of signaling could be larger.

Proposition 2 – A pooling PBE satisfying Cho-Kreps exists, for some parameter values.

Figure 1, panel (c) illustrates this. There is one pooling PBE in which both *C* and *N* firms do not signal. The case in which both signal is ruled out since, by definition, *N* firms cannot signal. In the pooling PBE, the market has the following Bayesian updating process: (1) if it observes some firms have high levels of inventory, it concludes that such firms have the *ex ante* probability of being competent, (2) if it observes firms have low levels, it concludes these firms are competent. The latter is the only out-of-equilibrium belief that can sustain a pooling equilibrium. Pooling is sustained if, for *C* firms facing signaling decisions (recalling that f is the fraction of high-inventory firms that are competent):

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

$$m \leq r_C.x_C / [(1 - f).(x_C - x_N) + r_C.x_C]. \tag{2}$$

Denote the break-even m as m_p. Pooling obtains when $m < m_p$. Depending on various values of f and g, it is easy to see that m_p could be greater than, equal, or less than m_s. Specifically, m_s is less than m_p if:

$$f < g.r_C.x_C / (x_C - x_N).$$

The various parameters, such as m, f, and x_C, are useful in determining the comparative statics, as follows. I confine the short discussion to the key ingredients for inventory to have a signaling role. Each maps to a comparative static—a prediction—that could be empirically tested.

- *Incentive for signaling.* The model requires the market to reward competence. Lower-inventory firms have higher valuation, all else being equal. The two-type model described, however, does not necessarily predict a monotonic relationship between inventory levels and valuation. Indeed, in Figure 1, panel (c), all low-inventory firms have x_C and all high-inventory firms have $f.x_C + (1 - f).x_N$. Therefore, the relationship might look like a step function. On the other hand, with continuous types, the relationship is monotonic (Lai (2005)). In reality, the situation is likely to be somewhere between these extremes. The test can falsify our signaling story if we observe that high inventory firms get better valuations.
- *Short-termism*. In the model, this is the m parameter. It is because of short-termism that firms may want to signal, to get better short-term valuation. The testable prediction is that industries that are more short-term will see more separation.
- *Information asymmetry*. This means that the stock market cannot tell if inventory is used to enhance fill rate or is the result of incompetence, while firms know (or think they do). What happens when asymmetry is reduced? First, the model predicts that when firms announce inventory write-offs, they reveal themselves as incompetent. Their stock prices drop. Since pooling happens in various degrees, the model further predicts that the drop in valuation could be larger than what the write-off amount itself might suggest. Furthermore, the greater is f and the larger is x_C compared with x_N, the higher is the pooled valuation compared with x_N. In this case, a write-off announcement would reduce the firm's valuation even more. In short, conditioning on inventory level, the market reaction is more severe if there is more pooling.

3. Empirical Tests

I test the three predictions just described. For signaling incentive, I check to ensure that higher-inventory firms do not get better valuations. For short-termism, I see if short-term industries have more separation. For information asymmetry, I test if inventory write-offs trigger "overly large" stock price drops. I also describe alternative explanations of the results, and how these are ruled out.

3.1. Signaling Incentive: Higher Inventory Firms Do Not Get Better Valuations?

I use the following specification:

$$(3)\quad VALUATION_{f,t+1} = \beta_0 + \sum_{lag=0}^{l} \beta_{lag}.VALUATION_{f,t\text{-}lag} + \beta_1.INVENTORY_{ft} + FIRM\text{-}EFFECTS_f + YEAR\text{-}EFFECTS_t + \mathbf{W_{ft}}\boldsymbol{\gamma_{ft}} + \varepsilon_{ft}\,,$$

where $VALUATION_{ft}$ is some 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 in many ways using inventory of various types, such as work-in-progress, finished goods), *FIRM-EFFECTS* and *YEAR-EFFECTS* are unobserved firm and year fixed effects, $\mathbf{W_{ft}}$ a vector of relevant controls, and ε_{ft} is assumed to be white noise. Specifically for $\mathbf{W_{ft}}$, I follow the more recent practice for q regressions, especially Gompers, et al. (2003), 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, I include log of net sales as a control too. To minimize endogeneity, I lag the right-hand-side, and include l lagged dependent variables. I report estimations with 0 and 3 lags, but the results are robust to other lag structures.

The data is obtained from a number of sources. From CRSP and COMPUSTAT, I obtain financial profiles of firms for years between 1950 and 2003. From IRRC, I obtain the governance index G. From Professor French's website, I obtain the factors for returns regressions. I then link all firm-year observations from these sources. I include only observations from manufacturing and the retail or wholesale sectors, since inventory is harder to interpret for other sectors. To rid the data of outliers, I winsorize values at 1% and 99%. Analyses without these two exclusions produce the same qualitative results (Lai (2005)). The estimation sample is summarized in Table 1. Because there are so few observations with governance index values, I report regressions without using these as regressors. In regressions reported in Lai (2005), the evidence is that including these does not change the results. Another concern is that observations dating back to the earlier years might be systematically different (*e.g.,* fewer, more likely to be measured with error). In unreported regressions, I regress with sub-samples excluding earlier data (1980- and 1990-2003) and produce the same results. In these sub-samples, I also use a Heckman sample selection correction that exploits the availability of earlier data, and still obtain the same qualitative results.

Table 2 reports estimates using four models: retail versus manufacturing and with zero versus three lags. The measure of *VALUATION* is Tobin's q. This has been used for firm valuation since Demsetz and Lehn (1985) and Morck, et al. (1988). I 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 I use the two-digit SIC classification for industry classification. In Lai (2005), I use the Fama and French (1997) forty-eight industries as classification and obtain the same results.

In all models, I would reject signaling incentive if the coefficient on *INVENTORY*, as measured by inventory/sales, is positively signed. The table shows that signaling incentive cannot be rejected. Indeed, the coefficient is negative and is modestly statistically and economically significant. In model (1), for example, the difference in predicted *q* between the lowest and highest inventory firms is 0.94, which is on the same order as the *q* mean (0.40) and standard deviation (1.65). This is consistent with an incentive to signal, although I hasten to add that just this alone is also consistent with alternative interpretations that I consider later. As expected, the results are more significant for retail industries, where inventory is a greater factor in valuation (Gaur, et al. (2005b)).

The estimation is robust to different measures, controls, or estimation methods:

1. *VALUATION*. Instead of *q*, I also measure valuation with buy-and-hold returns. The specifications for buy-and-hold return regressions follow those in Gompers, et al. (2003), in which I regress on *INVENTORY* as well as the usual Fama-French factors (*SML*, *HML*, *UMD*; please see next section).
2. *INVENTORY*. Instead of inventory divided by sales, I also scale inventory by assets. Further, I employ finer measures of inventory, at the level of materials, work-in-progress, and finished goods. I also add LIFO (last-in-first-out) reserves to inventory, so that all firms are put on an equivalent FIFO (first-in first-out) basis. A final set of measures follows Chen, et al. (2005), calculating abnormal inventory using inventory days (inventory scaled by cost of goods sold) and inventory/assets.
3. Control variables. Apart from the governance index, I use an indicator for whether the firm has undergone an acquisition or merger in any year prior to that of the observation, indicators for the identity of the auditor of the firm, indicators for different audit opinions (classified into unaudited, unqualified, qualified, disclaimer or no opinion, unqualified with explanatory language, and adverse opinion), and inventory valuation methods (no inventory; FIFO; LIFO; "specific identification'; average cost; retail method; standard cost; current or replacement cost; not reported). I also include the regressors for inventory turns in Gaur, et al. (1999): capital intensity, gross margin, and sales surprise.
4. Estimation methods: Besides dealing with potential heteroscadasticity using Huber-White robust standard errors, I manage potential correlation with clustering. In fixed effects estimations, I test if random effects might be more appropriate, with Hausman tests. In return regressions, I use the

standard Fama and Macbeth (1973) framework. Finally, I model the innovations with an AR(1) process to account for potential serial correlation in the disturbances.

Estimations with the above variations do not qualitatively change the findings and are not reported here (but see Lai (2005)). In short, *VALUATION* could be explained by *INVENTORY*, after controlling for observed and even time-invariant unobserved factors. Yet, the result could still be explained by stories other than signaling. One example is that the market could be inefficient, over-valuing low-inventory firms. However, none of the alternative explanations involves short-termism and information asymmetry, so tests of these can be used to rule out the non-signaling stories.

3.2. Short-termism: Firms in Short-term Industries Separate More?

I measure short-termism with some variables standard in the corporate finance literature (*e.g.*, Core, et al. (1999), Ritter and Welch (2002)). Specifically, I consider short-term holdings of stocks and options and long-term incentive plans. The data is from ExecuComp, which has data on the top 5 executives in each firm. I calculate the following for the average executive in each industry-year: (1) for stock holdings, the restricted stock holdings or the percent of company stock held, (2) for options, the value realized from options exercised, and (3) for long-term incentives, the amount paid based on firm performance over at least one year (usually three years). All are scaled by total compensation, including stock and options granted. For robustness, I use a variety of other measures, such as the value of options granted (rather than exercised) valued with the Black-Scholes formula, or the value of in-the-money options exercised and that unexercised. I also scale with total compensation excluding options, and total excluding both stocks and options. These produce similar results and are not reported here. These variables are shown as *SHORT-TERMISM* in the following specification, indexed by *s*, while industry is indexed by *i*:

$$(4)\ VALUATION_{f,i,t+1} = \beta_0 + \sum_{lag=0}^{l} \beta_{lag}.VALUATION_{f,i,t\text{-}lag} + \beta_1.INVENTORY_{fit} +$$
$$\sum_{s\in\{short-termism\}} [\beta_{s1}.INVENTORY_{fit}.SHORT\text{-}TERMISM_{sit} + \beta_{s2}.SHORT\text{-}TERMISM_{sit}] +$$
$$FIRM\text{-}EFFECTS_f + \mathrm{I}(YEAR_{f,it}) + \mathbf{W_{ft}\gamma_{ft}} + \varepsilon_{ft}\ .$$

The prediction is that β_{s1} is negative for stock and options holdings and non-negative for long-term compensation. Table 3 shows the results. For retail, shown in model (1), the signs are as predicted and are statistically significant. They are also economically significant. For stock holdings, the coefficient of -1.973 translates to this: one standard deviation in stock holdings is correlated with greater sensitivity (54% of the standard error) of *VALUATION* to *INVENTORY*. For manufacturing, in model (2), the result is murkier. This is because I do not have sufficient number of observations on executive compensation. However, the signs on the interactions are all as predicted. Further, the only significant coefficient, on the interaction of *INVENTORY* and long-term compensation, is non-negative as predicted. In model (3), I use a different definition of stock holdings—the percent of company stock held by the average executive in the industry-year. As before, all the interaction variables are correctly signed. Only one coefficient, the interaction of *INVENTORY* with options, is significant, and it is signed as predicted.

Overall, I interpret these findings as consistent with a signaling theory, but not with alternative stories that do not have a managerial myopia component.

3.3. Information Asymmetry: Do Write-offs Trigger "Overly Large" Stock Price Drops?

Although there is much work in the accounting literature that tests the impact of write-offs (usually of bad capital investments), there is no consensus on what that impact this. Three contending viewpoints seem to have emerged: a "favorable resolution" story, a "bad news" one, and an "irrelevance" story (see Elliott and Shaw (1988), Francis, et al. (1996)). "Favorable resolution" predicts that the market reacts *positively* to write-offs, which are seen as signals that firms are honest and have put the worst behind them. "Bad news" predicts a *negative* reaction, treating write-offs as revealing the bad state of firms. "Irrelevance" predicts no reaction, viewing write-offs as *ex post* reactions to changes in fundamental conditions.

Not only is the accounting literature ambiguous about what is predicted, it is also not instructive for my test, because the literature mostly treats write-offs in aggregate terms rather than specific to inventory. There are two exceptions. 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 their paper, they do report a 31.7% drop in excess return over days -1 and 0. For our purpose, however, their result is less informative for three reasons. First, their analysis pre-dates recent innovations in event analysis, such as the use of Fama-French factors and industry controls. Second, they do not consider the magnitude of the write-off, only whether an announcement is made. Finally, their test makes no prediction about differences in reaction between separating and pooling PBEs.

The second noteworthy work, 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. As the focus of their study is not on inventory, their classifications of cause or consequence is not specific to inventory levels or quality. Another difference is in methodology, given the different research questions. I control for potential confounding informational effects in announcements, such as simultaneous announcements of earnings forecasts. I also test for reaction magnitudes conditioning on write-off amount.

I conduct the information asymmetry test in four parts. The first is whether market reaction is negative, consistent with the signaling story that write-off announcements reveal that firms are incompetent ("bad news" story, versus the other two). The second part is to check if the market reaction is *bigger* than what the write-off amount implies if there were no signaling. This rules out any interpretation that the negative market reaction is a simple response to reduced cash flow expectations, without a signaling story. This second part of the test could still be subject to a competing explanation that there is a "torpedo" effect (Skinner and Sloan (2002)), in which bad announcements are severely punished for growth firms which under-deliver on analyst expectations. To rule this out, the third part of the test is on the subset of non-growth firms. To seal the signaling story, the fourth part of the test checks if market reaction is more negative for industries that have more pooling.

I use event analyses, but need to strip the announcement of confounding informational effects. Like all tests of this nature, this is really a joint test of market efficiency (does the market react quickly?) and the null hypothesis of interest (does the market react negatively?). Fortunately, this is not an issue here since I am only interested in one side of the test. If I find that the market reacts negatively, then there is evidence that inventory write-offs are informationally negative (the test of interest). If I do not find negative reaction, I cannot rule out the joint hypotheses (not a test of interest).

I start by considering what might potentially confound the link between write-offs 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 wrongly attributed to write-offs.

The first two issues have largely been addressed in the accounting literature. The consensus is that firms do manipulate the timing of disclosures, but this does not have significant effects on market reactions. The main reasons are that manipulation is limited due to litigation risks (*e.g.,* Skinner (1994), Barth, et al. (2001)) and market efficiency, which ensures that the market factors in manipulation *ex ante* (*e.g.,* Kothari, et al. (2005)). There is another way to manage the first issue, by exploiting an institutional detail. In March 1995, the accounting standards board issues SFAS No. 12 that provides less discretion on write-off decisions. Although the note focuses on long-lived assets, inventory write-offs after that ought to be less (but obviously not totally) discretionary. Therefore, I estimate the regressions here using a sub-sample after that date, correcting for truncation. The results are similar and not reported here.

To tackle the third issue, I construct a sample rid of confounding news. I first obtain all 133,122 footnotes from First Call, and after manual inspection of the footnotes, decide to screen for those with the word "invento" (for inventory, inventories, *etc.*) 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." To ensure quality of the data, the items screened out and retained are manually inspected to ensure proper exclusion. This removes one that is also associated with "facility closure," another with "restructuring," a third with "product recall."

To eliminate the confounding impact of simultaneous earnings announcements, I restrict the sample to announcements in which there are no earnings surprises. In the results reported, I define "no surprise" as when the analyst mean consensus of expected earnings, from I/B/E/S, is within 5% of actual earnings. Other thresholds, at 0%, 1%, and 10%, do not change the qualitative results and are unreported. I also check that there are no confounding acquisitions or stock splits. If there is more than one footnote in a year, I remove all but the earliest of these. Table 4 shows the summary statistics of the sample footnotes.

An important consideration is whether the culling of the announcements leads to sample selection bias. I use a Heckman correction procedure, with a selection model as follows:

$$SELECTED_{ft} = f[WRITE\text{-}OFF_{ft}, MKTCAP_{ft}, FPE_{ft}, \mathrm{I}(PERIODICITY_{ft}), \mathrm{I}(SIC_{ft})] ,$$

where the regressors are the write-off amount, market capitalization, fiscal end-date of the announcement, indicators for periodicity (*e.g.*, quarterly or annually) and the two-digit SIC code.

Next, I measure abnormal stock market reaction—*i.e.,* that stripped of the usual explanatory factors such as risk. The factors that are partialled out are those proposed by Fama and French (1993) and Carhart (1997):

$$R_{it} - R_{ft} = \alpha_t + \beta_t(R_{mt} - R_{ft}) + s_t SMB_t + h_t HML_t + u_t UMD_t + \varepsilon_{it} ,$$

where R_{it} is the return for the ith stock at time t, R_{ft} the risk-free return, R_{mt} the market return, SMB_t the small-medium-large factor, HML_t the high-medium-low factor, and UMD_t the momentum factor. The data is from CRSP-COMPUSTAT and Kenneth French. I use a monthly frequency and an estimation window of 6 months. Estimations using daily data and other estimation windows, as well as other estimation models using CRSP-indexed value- and equal-weighted models, all produce the same qualitative results (see Lai (2005)).

I calculate two versions of what the drop might be in a non-signaling context. In a less conservative version, I impute the "bad" inventory dollar-for-dollar into the market value of the firm. In a more conservative version, I impute the write-off amount as an earnings drop. In this version, the market assumes that the write-off is the beginning of what is going to be a regular hit on the earnings of the firm. To translate the write-off into market return, I use the previous-month price-earnings ratio. This takes care of the worry that the drop in valuation is really about the market's worry that there are more write-offs to come. In this paper, I report the latter more conservative version. Unsurprisingly, the less conservative version yields stronger evidence for signaling.

Table 5 shows the results of the four parts of the test: (1) market reaction is negative, (2) is more negative than signaling were not present, (3) is not explained by the torpedo effect, and (4) has cross-sectional interactions with the degrees of pooling.

The first test results are on the vertical axis of panel (a), which shows the actual market reaction. Almost all announcements lead to drops in stock price, thus supporting the "bad news" story about write-off announcements. Of the 34 announcements with sufficient information for analysis, only 2 lead to a stock price increase. The mean post-announcement stock price is only 67% of the pre-announcement price (recall that this is after adjusting for all Fama-French factors). The p-value that the statistic is less than 100% is 0.0000, and the t-statistic is -8.92.

The second test result is also in panel (a), now looking at both axes. Each announcement is a dot, comparing its actual and non-signaling post-announcement stock prices, or equivalently (since there are no stock splits), market valuation. Specifically, the ratio is 0.78, and is statistically significant. The t-statistic is -2.67. In other words, the actual post-announcement valuation is only 78% of what the write-off amount implies, even if the latter is aggressively considered to be an annual hit thereafter.

In the third test, I remove all firms in purportedly "growth" industries (biotechnology, drugs), I obtain the same qualitative results. The average ratio of actual to non-signaling is 0.79, the t-statistic for a test against unity is -2.06, p-value 0.025.

Results of the fourth test are in panel (b). In the former, I use the sensitivity of q to inventory as an observable indication of whether firms tend to pool. In industries with more pooling (sensitivity is below the median), the model predicts that the post-announcement stock price is lower than that for separating ones. The result shows that firms in "pooling" industries suffer a lower valuation, at 0.64 of the valuation imputed by the write-off amount alone, compared with 0.77 for "separating" industries.. Because of the small number of observations, the t statistic of the difference is not high.

To wrap up, I report the results of the Heckman correction procedure to check that there is no sample selection bias in constructing the announcements dataset. The results still stand; indeed the key results are stronger. For example, the mean ratio of actual to non-signaling post-announcement stock price is lower, at 0.76, compared to the uncorrected result of 0.78.

4. Discussion and Conclusion

I propose that in a world with signaling incentives, short-termism, and information asymmetry, inventory has a signaling role. Firms and the stock market understand this, resulting in separating or pooling equilibria. This is one channel in which inventory translates into market valuation. I document empirical evidence that is consistent with this signaling story and at the same time rules out competing explanations. It would be intriguing to investigate the extent to which this theory of how one operational parameter, inventory, translate into market valuation might be generalizable to other operational parameters that have the same properties of signaling incentives, short-termism, and information asymmetry.

One must bear in mind that there would be situations in which the above story would *not* apply. For example, some firms like Neiman Marcus might be able to credibly communicate a high-responsiveness position to the stock market, and maintain a high-inventory position.[3] Other examples might be include firms that are covered by institutional investors, who might be more savvy about firms' strategies than retail investors (Gompers and Metrick (2001)).

Conversely, and more speculatively, the theory might be a parsimonious explanation for a range of disparate, observed phenomena. First, it already explains how write-off announcements might lead to bigger drops in market value than what the write-off amounts alone might suggest. Second, the theory potentially explains why some high-responsiveness firms, from the Ritz Carlton and Coutts (the private bank) to Brooks Brothers and Neiman Marcus, are or have to be privately-held, at least for long periods of their history.[4] In the financial services industry, according to Forrester Research (Beasty (2005), "whether it's banks, brokerages, or insurers, the privately owned institutions always do better at these [customer advocacy] rankings." Third, the theory could provide an additional explanation for why stock-outs might be pervasive (*e.g.*, Gruen, et al. (2002), Verbeke, et al. (1998)) even among *competent* firms[5]. If technological advance and investments are proxies for competence, it seems that increases in competence have not increase fill rate much. In 1968, *Progressive Grocer* reports that 20% of shoppers face stock-outs. About forty years of technological advances later, roughly "a third of the consumers entering a store are [still] looking for a specific item but fail to buy because they cannot find it" (Wharton at Work, 2002). Cross-sectionally, Gruen, et al. (2002) also reveal that the fill rate for Europe, the U.S., and other parts of the world are about the same, despite their different competence levels. Although there could be other explanations, this situation is consistent with the view that competence alone is not a strong predictor of high fill rates. It would be a natural extension to confirm the implication of the theory advanced here with international data, where there is variation in the degrees in the incentive to signal, short-termism, and information asymmetry.

Yet another natural direction is to look at 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)). Or at

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[3] I thank Walter Salmon for suggesting this example.

[4] 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). Neiman Marcus was taken private by the Texas Pacific Group and Warburg Pincus LLC in October 2005. So was Brooks Brothers, by Claudio Del Vecchio.

[5] A competing explanation, for example, is that product variety has increased (*e.g.* Gupta and Srinivasan (1998), Randall and Ulrich (2001)).

signaling phenomenon over time. For example, during the take-over wave of the 1980s, we expect that firms are more myopic and tend to signal their competence with lower inventory, even among competent firms pursuing high fill rate strategies. At these times, short-term valuation can be used as currency for acquisitions or defense against takeovers. It would be interesting to check if this is true.

Finally, the model has been worked out as if the firm is a monolithic, aligned entity, without agency problems between managers and shareholders. Suppose managers are keen to not only increase share price for 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). Agency theory does not seem to have a clear prediction of how the theory presented here might be modified. This could also be an interesting area for further research (see Kocabiyikoglu and Popescu (2005) for a recent study, involving different contracts between shareholders and managers).

What is the implication of all this for firms? Any answer must obviously be set in the context of the firms' other priorities. All things being equal, one set of implications is about how to better manage valuation. Specifically, how can firms credibly communicate the motives for high fill-rate (and more generally, high responsiveness) strategies? One example is to commit irrevocably to these strategies (*e.g.,* Ghemawat (1991)). There is also the perennial question of the appropriate balance between short- and long-term goals. The theory sheds light on the implications of short-termism, and it would be appropriate to consider them in the context of the costs and benefits of long-term goals. Interestingly, compensation plans is one area where firms can more credibly reveal their degree of short-termism to the stock market.

Another set of implications is about getting publicly listed and be subject to pressures of the stock market. The theory brings to light how going public might affect operational decisions.

Finally, there might be implications for policy makers. An important consideration is what the social welfare considerations are, and whether, for example, inventory disclosures ought to have the kind of details (*e.g.,* aging records) like Basel requirements for loan portfolios in banks.

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Figure 1—Model in Pictures

There are two types of firms, *C* for competent and *N* for incompetent. *f* is the proportion of *C* firms among high-inventory ones (right of the vertical dashed line), and *g* is the proportion of competent firms that might separate.

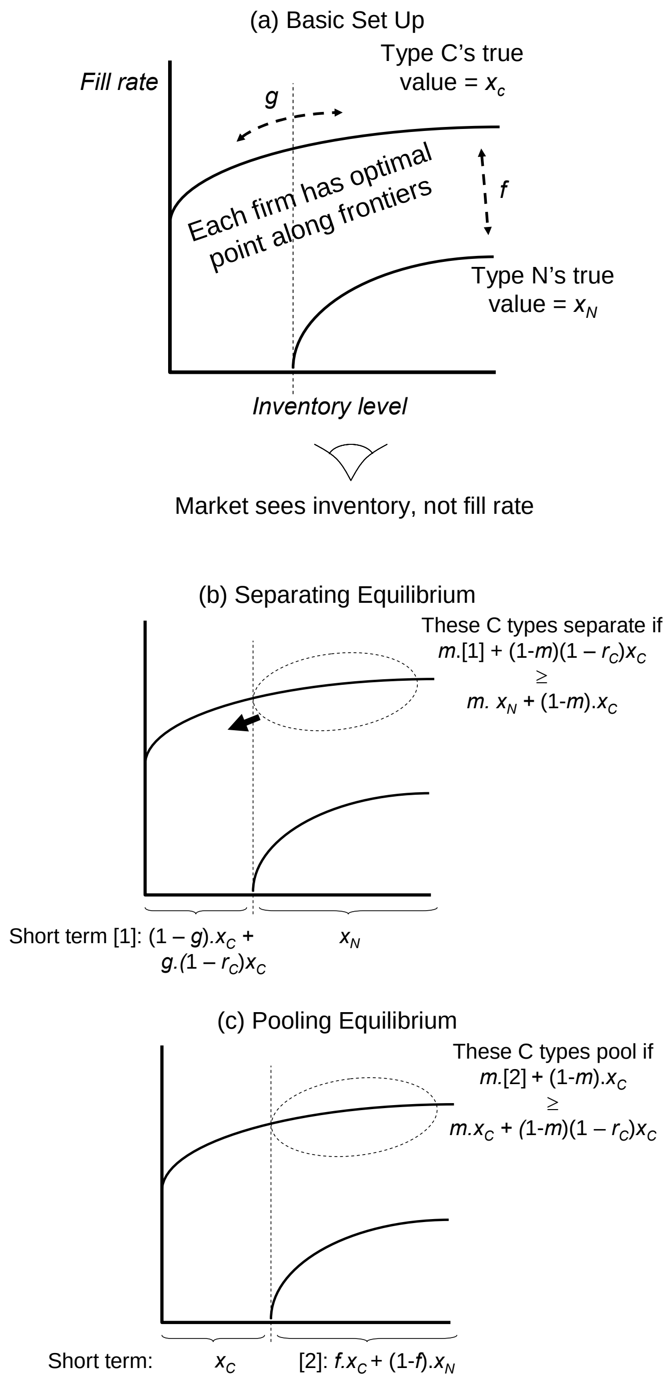


Table 1—Summary Statistics of Sample for Valuation Analysis

The data is from the merged CRSP-COMPUSTAT tapes, IRRC, I/B/E/S, and ExecuComp. Only observations from manufacturing and the retail or wholesale sectors are included. The data is also winsorized at 1% and 99%. The data is for firms from 1950 through 2003.

	Obs	Mean	Std. Dev.
Year	57,485	1,984.9	12.4
Net sales ($M)	57,485	1,453.6	3,770.1
q	57,485	4.3	6.7
Op Income before depr ($M)	55,870	173.3	858.7
Inventory - total ($M)	56,056	161.2	617.8
Inventory – materials ($M)	26,377	45.7	236.0
Inventory – work in prog ($M)	23,862	16.9	76.9
Inventory – finished goods ($M)	25,290	62.3	214.4
Inventory – LIFO reserves ($M)	40,820	22.0	159.0
Age	57,485	11.5	10.3
Market cap ($M)	56,069	1,291.8	8,091.7
Receivables ($M)	55,746	162.1	880.7
Payables ($M)	50,581	130.3	677.3
Plant, property, equipment ($M)	54,853	82.9	414.9
Working cap ($M)	55,624	123.4	503.4
S&P 500	57,485	0.1	0.3
G index	2,137	9.2	2.8
Acquisitions	57,485	0.1	0.3

Table 2—Higher Inventory Firms Do Not Get Better Valuations?

The specification is:

$$VALUATION_{f,t+1} = \beta_0 + \sum_{lag=0}^{l} \beta_{lag}.VALUATION_{f,t-lag} + \beta_1.INVENTORY_{ft} + FIRM\text{-}EFFECTS_f + YEAR\text{-}EFFECTS_t + \mathbf{W_{ft}\gamma_{ft}} + \varepsilon_{ft}\,,$$

where $VALUATION_{ft}$ is some suitable measure of the value of firm *f* at time *t*, $INVENTORY_{ft}$ is scaled by sales, *FIRM-EFFECTS* and *YEAR-EFFECTS* are unobserved firm and year fixed effects, $\mathbf{W_{ft}}$ a vector of relevant controls, and ε_{ft} is assumed to be white noise. The dependent variable, *VALUATION*, is measured using the industry-adjusted median *q*, which is the firm *q* minus industry-mean, where I use the 2-digit SIC code for industry classification. *INVENTORY* is measured using inventory/sales. $\mathbf{W_{ft}}$, includes log assets, log firm age, an indicator that is 1 if the firm is in the S&P 500, and log net sales. All estimations are done with lagged right-hand-side variables, firm and year fixed effects, with Huber-White robust standard errors and clustered around firms. These estimations are also robust to other performance measures, other controls, different ways of industry classification (please see text).
*** Significant at the 1% level, ** at 5%, * at 10%. Figures in brackets are standard errors.

	Retail	Manufacturing	Retail	Manufacturing
	(1)	(2)	(3)	(4)
Inventory (scaled by sales)	-1.170 (.340)***	-.847 (.390)**	-.561 (.247)**	-.604 (.314)*
Log assets	-.292 (.076)***	-.369 (.068)***	-.157 (.039)***	-.183 (.052)***
Log firm age	-.462 (.057)***	-.474 (.052)***	-.136 (.054)**	-.219 (.052)***
Log sales	.018 (.067)	.010 (.055)	.012 (.027)	-.060 (.046)
S&P 500	-1.222 (.157)***	-.707 (.247)***	.242 (.121)**	-.387 (.109)***
Constant	2.048 (.320)***	1.750 (.148)***	.458 (.314)	1.059 (.117)***
Lagged dependant variables	0	0	3	3
N	18198	26619	14079	21071
Adj. R squared	39.2%	48.2%	54.4%	60.3%
p-value	.0000	.0000	.0000	.0000

Table 3—Firms in Short-term Industries Separate More?

The specification is:

$$VALUATION_{f,i,t+1} = \beta_0 + \sum_{lag=0}^{l} \beta_{lag}.VALUATION_{f,i,t-lag} + \beta_1.INVENTORY_{fit} +$$

$$\sum_{s\in\{short-termism\}} [\beta_{s1}.INVENTORY_{fit}.SHORT\text{-}TERMISM_{sit} + \beta_{s2}.SHORT\text{-}TERMISM_{sit}] +$$
$$FIRM\text{-}EFFECTS_f + YEAR\text{-}EFFECTS_t + \mathbf{W_{ft}\gamma_{ft}} + \varepsilon_{ft} \,,$$

where $VALUATION_{fit}$ is some suitable measure of the value of firm f in industry i at time t; $INVENTORY_{ft}$ is scaled by sales; $SHORT\text{-}TERMISM_{sit}$ is measure s of how short-term are firms in industry i; *FIRM-EFFECTS* and *YEAR-EFFECTS* are unobserved industry, firm, and year fixed effects; $\mathbf{W_{ft}}$ a vector of relevant controls, and ε_{ft} is assumed to be white noise. The dependent variable, *VALUATION*, is measured using the industry-adjusted median q, which is the firm q minus industry-mean, where I use the 2-digit SIC code for industry classification. *INVENTORY* is measured using inventory/sales. *SHORT-TERMISM* is measured with three variables: stock holdings, options holdings, and long-term compensation. In models (1) and (2), these are the averages per executive in the industry-year in the restricted stock holdings, the value realized from options exercised, and the amount paid based on firm performance over at least one year. In model (3), as a variation, stock holdings are measured as the percent of company stock held. All *SHORT-TERMISM* variables are scaled by the executive's total compensation, including stocks and options. $\mathbf{W_{ft}}$, includes log assets, log firm age, an indicator that is 1 if the firm is in the S&P 500, and log net sales. All estimations are done with firm and year fixed effects, with Huber-White robust standard errors and clustered around firms. These estimations are also robust to other performance measures, other controls, different ways of industry classification (please see text).
*** Significant at the 1% level, ** at 5%, * at 10%. Figures in brackets are standard errors.

	Retail	Manufacturing	Manufacturing
	(1)	(2)	(3)
Inventory	-4.987 (1.509)***	.981 (1.571)	-2.268 (3.096)
Inventory x stock holdings	-1.973 (.664)***	-.103 (.686)	
Inventory x % company stock held			-.171 (.475)
Inventory x options exercised	-1.671 (.646)**	-.255 (.632)	-1.274 (.557)**
Inventory x long-term compensation	.020 (.198)	.780 (.396)**	.231 (.406)

Table 4—Summary Statistics of Sample for Event Analysis

The data is matched from First Call (footnotes), I/B/E/S (estimated and actual earnings), and CRSP-COMPUSTAT (financials). In this sample, footnotes exclude those with earnings surprises (mean analyst estimates exceeds 5% of actual earnings per share) and confounding announcements (*e.g.,* restructuring, recalls, facility closures).

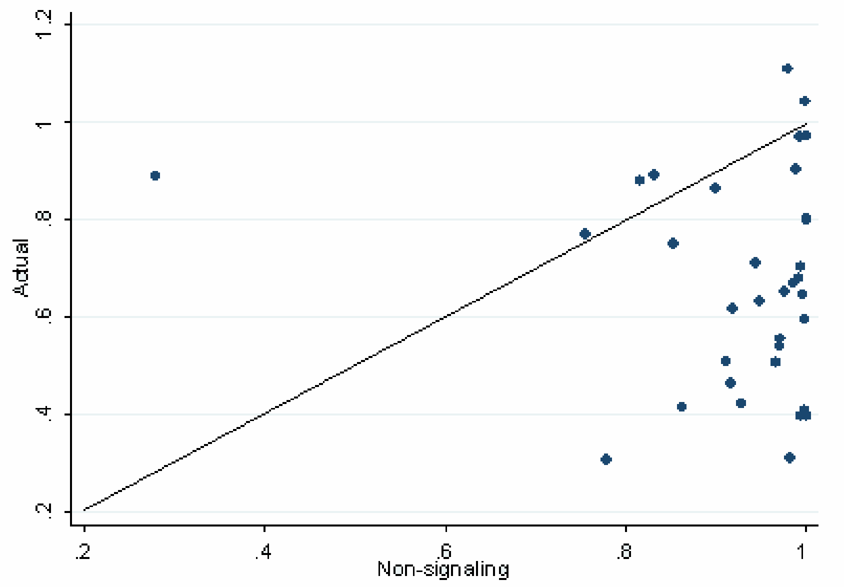
	Firm	Announced	Write-down $mil	Industry
1	Advanced Neuromodulation System	13-Aug-97	0.03	MEDICAL SUPPLIES
2	Alaris Medical Systems Inc	17-Nov-93	0.11	DRUGS
3	Alberto-Culver Co	31-Jul-95	0.02	COSMETICS
4	DIMON Inc	24-Aug-98	0.11	TOBACCO
5	Angeion Corp	19-Jan-99	0.08	MEDICAL SUPPLIES
6	Anheuser-Busch Companies Inc	11-Oct-96	0.09	BEVERAGES
7	Beverly Enterprises	20-Feb-96	0.27	HOSPITALS
8	Bioject Medical Technologies In	25-Jun-99	0.01	MEDICAL SUPPLIES
9	Brothers Gourmet Coffees Inc	18-Aug-98	0.08	FOOD PROCESSORS
10	Cantel Medical Corp	25-Mar-03	0.90	MEDICAL SUPPLIES
11	Cavalier Homes Inc	27-Jul-00	0.40	LEISURE PRODUCTS
12	Cell Tech International Inc	13-Nov-98	0.90	MEDICAL SUPPLIES
13	Chiquita Brands International I	11-Oct-94	1.10	FOOD PROCESSORS
14	Endologix Inc	30-Jan-98	2.00	MEDICAL SUPPLIES
15	Enpath Medical Inc	22-Jul-03	0.03	MEDICAL SUPPLIES
16	Exide Technologies	30-Jan-01	0.18	AUTO PART MFG
17	Falcon Products Inc	3-Sep-98	0.31	HOME FURNISHINGS
18	First Alert Inc	28-Nov-95	0.08	HOME FURNISHINGS
19	Fortune Brands Inc	14-Sep-93	0.09	HOME PRODUCTS
20	Galaxy Nutritional Foods Inc	29-Jun-00	0.90	FOOD PROCESSORS
21	Gish Biomedical Inc	15-Nov-99	0.06	MEDICAL SUPPLIES
22	GTECH Holdings Corp	9-Mar-95	1.06	LEISURE PRODUCTS
23	Innovative Clinical Solutions I	14-Sep-99	1.49	SERVICES TO MEDICAL PROF
24	Interferon Sciences Inc	15-Apr-98	0.55	BIOTECHNOLOGY
25	International Comfort Products	15-Aug-95	0.06	EAFE APPLIANCES
26	Vista Medical Technologies Inc	28-Jan-99	0.04	MEDICAL SUPPLIES
27	Knape & Vogt Manufacturing Co	1-Sep-98	0.13	HOME FURNISHINGS
28	LaserSight Inc	30-Mar-01	0.20	MEDICAL SUPPLIES
29	Laserscope Inc	22-Oct-96	0.37	MEDICAL SUPPLIES
30	William Lyon Homes	21-Aug-92	0.84	HOME BUILDING
31	McClain Industries Inc	21-May-01	0.70	AUTO PART MFG
32	Meridian Bioscience Inc	14-Nov-01	0.08	DRUGS
33	Isolyser Company Inc	13-Nov-97	0.33	MEDICAL SUPPLIES
34	Nam Tai Electronics Inc	30-Jul-01	0.67	HOME FURNISHINGS
35	Nanogen Inc	29-Oct-03	0.04	BIOTECHNOLOGY
36	Northland Cranberries Inc	22-May-00	27.00	FOOD PROCESSORS
37	Oca Inc	19-Mar-03	4.20	HOSPITALS
38	OPTA FOOD INGREDIENTS INC	25-Oct-01	0.07	FOOD PROCESSORS
39	Optical Sensors Inc	5-Nov-97	0.50	MEDICAL SUPPLIES
40	Physiometrix Inc	1-Nov-01	0.37	MEDICAL SUPPLIES
41	Pilgrim's Pride Corp	9-Mar-00	0.09	FOOD PROCESSORS
42	Polaroid Corp	9-Jun-98	0.51	LEISURE TIMES
43	Premium Brands Inc	11-Apr-02	1.60	FOOD PROCESSORS
44	RCS INVESTIMENTI S.p.A.	3-Aug-98	0.57	CLOTHING
45	Revlon Inc	8-Oct-99	280.00	COSMETICS
46	Royal Grip Inc	8-Aug-95	0.13	LEISURE PRODUCTS
47	Sicor Inc	14-Aug-97	2.60	DRUGS
48	JM Smucker Co (The)	17-Feb-00	0.11	FOOD PROCESSORS
49	Synthetech Inc	12-Nov-02	0.06	BIOTECHNOLOGY
50	TL Administration Corp	29-Nov-00	16.00	FOOD PROCESSORS
51	Trans Max Technologies Inc	12-Jul-01	0.16	LEISURE TIMES
52	Vans Inc	28-May-02	2.40	CLOTHING
53	Vivus Inc	15-Oct-98	0.50	MEDICAL SUPPLIES
54	Wyeth	18-Oct-99	0.07	DRUGS
55	Zymetx Inc	13-Oct-00	0.90	BIOTECHNOLOGY

Table 5—Do Write-offs Trigger "Overly Large" Stock Price Drops?

Panel (a) – Actual versus "Non-Signaling" Stock Price Drop

The axes show actual (vertical) versus imputed (horizontal) drop in share price in the month of an inventory write-off announcement, in fractional terms - ***e.g.,*** 0.8 means 20% drop. Inventory write-offs obtained from First Call footnotes, culled using a set of phrases (see paper). Footnotes that might be confounded with earnings surprises and other confounding events (e.g., product recalls) are excluded. The remaining inventory write-off announcements are used in an event analysis using a Fama-French-Carhart four factor model (SML, HML, UMD) at the monthly frequency, using data from Ken French and the merged CRSP-COMPUSTAT tapes. The estimation window is 6 months. The actual drop is calculated from the intercept of the predicted excess-return regression. The imputed drop is calculated by conservatively attributing the inventory write-off fully to earnings drop, and using the previous-month earnings-price ratio to calculated the drop in share price.

Actual / non-signaling average ratio = .78 (test against unity: *p*-value .0006, *t*-statistic -2.67, *N*=34)



(b) – Ratio for Separating and Pooling Industries

For each industry, the *q* sensitivity to inventory (per the earlier specification) is estimated. The announcements are then assigned and ranked by their industries' sensitivity. Announcements above the median sensitivity are interpreted to be in industries in which firms are more likely to separate. The means below are mean ratios of actual to non-signaling drops in stock price, calculated for announcements in separating and pooling industries.

	N	Mean	S.E.	*t*
More separating	18	.77	.16	
More pooling	19	.64	.07	
Difference		.13	.17	.74