When, and why, is inventory growth bad?

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June 25, 2013

Abstract

There is a well-known negative relation between inventory growth and future firm performance. An extensive literature has sought to attribute this negative relation to earnings management, diminishing marginal returns to new investments and risk. We provide new evidence on the negative relation between inventory growth and future firm performance by utilizing information external to the firm. Specifically, we show that when inventory growth for a firm is accompanied by asset growth in related firms, the negative relation between inventory growth and future firm performance is greatly attenuated. This evidence suggests that the lower persistence of accruals (i.e., inventory growth) is attributable to sub-optimal investment decisions, rather than risk, which the stock market and analysts do not incorporate in a timely manner.

JEL classification: G12; G14; M41
Key words: inventory growth, accruals, profitability, stock returns, supply chain.

We are grateful to seminar participants at London Business School and to Maria Correia, Gerben de Zwart, Vito Gala, Francisco Gomes, Daniele Scognamiglio and Ahmed Tahoun for helpful discussion and comments. Any errors are our own.

1. Introduction

In this paper we revisit the negative relation between accruals and future firm performance. Past research has offered a variety of reasons for this negative relation. Sloan (1996) documents that the accrual component of earnings is less persistent than the cash flow component of earnings. Sloan then suggests that this differential persistence in earnings components explains the negative relation between accruals and future firm performance. Subsequent research has offered a variety of alternative competing explanations for this negative relation: (i) diminishing marginal returns to new investment (e.g., Fairfield, Whisenant and Yohn, 2003; Richardson, Sloan, Soliman and Tuna, 2006; and Zhang, 2007), (ii) accounting distortions and earnings management (e.g., Xie, 2001, Richardson, Sloan, Soliman and Tuna, 2005), (iii) risk (e.g., Kahn, 2008; Wu, Zhang and Zhang, 2010), and (iv) transaction costs (e.g., Mashruwala, Rajgopal and Shevlin, 2006).

To help improve our understanding of why firms grow the scale of their working capital, and in particular inventory, we look to information outside the firm itself. There is a growing literature exploring the *unconditional* information content in supply chains. For example, Menzly and Ozbas (2010) find that knowledge of the supply chain linkages between industries is useful to generate superior forecasts of firm performance. Specifically, Menzly and Ozbas document a lagged response between downstream and upstream industry relative performance. For a given firm, if the downstream industries that you sell your output to are expected to perform better, as measured by recent stock returns and analyst revisions, then you (the upstream firm) are expected to perform better relative to firms whose products are sold to downstream industries expected to perform less well. Likewise, Cohen and Frazzini (2008) show that knowledge of firm-level customer-supplier relations is also useful to form superior unconditional forecasts of firm performance. Cohen and Frazzini show that for a given supplier firm if the downstream customers are expected to perform better, as measured by recent stock returns and analyst revisions, then the upstream supplier firm performs better relative to supplier firms whose products are sold to downstream firms expected to perform less well.

We extend this literature by making *conditional* use of the supply chain information. Using a large sample of US firms over the period 1988-2010, we find that information extracted from the Bureau of Economic Analysis on the make and use of commodities across industries is important in attenuating the negative relation between inventory growth and future firm performance. Belo, Gala and Li (2012) follow a related approach and extract industry level linkages to government end use and find that industry exposure to government spending is associated with future firm performance. They show that during Democratic presidencies, firms with high government exposure experience higher cash flows and stock returns, while the opposite pattern holds true during Republican presidencies. We extend this approach of extracting conditional information from industry linkages to focus on general firm level patterns of profitability.

We focus on inventory growth as our measure of accruals for several reasons. First, past research has shown that inventory growth demonstrates the strongest negative association between accruals and future firm performance (Thomas and Zhang, 2002; Hribar, 2002). Second, by identifying the explicit supply chain dynamics across firms we are able to corroborate real investment decisions across linked firms, and hence our conditioning information is related to real investment growth. Inventories are the real investment component of traditional measures of accruals.

A key feature of our research design is its ability to refute risk based explanations for the negative relation between inventory growth and future stock returns. There is sound asset pricing theory supporting the notion that the realization of growth options through real investment decisions, such as inventory growth and other non-current asset growth, should be associated with a lowering of expected returns (see e.g., Cochrane, 1991; Wu, Zhang and Zhang, 2010). However, our finding that the negative relation between inventory growth and future stock returns is weaker (stronger) for firms with relatively strong (weak) contemporaneous asset growth in related firms, is hard to reconcile with a risk based explanation. First, the cross-sectional dispersion in inventory growth across firms sorted on the basis of related firm real investment activity is similar. That is, the cross-sectional variation in inventory growth is similar for firms in industries where investing activity in related firms is either relatively low or high. So it is not the case that the firms with the weaker negative relation between inventory growth and future returns have less dispersion in their inventory growth. Second, the risk based argument would have to incorporate explicit views on supply chain dynamics and link that to the riskiness of the growth options that are realized through real investment decisions. While it is possible to make the argument that investment along the supply chain affects risk, a risk based explanation would also have to incorporate time variation as the same firm may face growth or contraction in related firms, depending on the decisions of those related firms at a point in time. Investment decisions of related firms are, at least partially, exogenous to the investment decisions of the firm itself. A more natural interpretation of the stronger negative relation between inventory growth and future stock returns for firms that are growing when there is relatively little investment growth in related firms, is that these firms are engaging in sub-optimal investment decisions.

For a sample of 555,696 US firm-months over the 1988-2010 period, we find that knowledge of real investment decisions in related firms helps condition the negative relation between inventory growth and future firm performance. To do this, we convert the MAKE and USE tables provide by the Bureau of Economic analysis into balanced industry level input-output tables. A full description of how we do this is contained in section 2.1. The resulting industry level input-output table is then the basis for cross-sectionally ranking industries, and constituent firms, into groups based on the level of contemporaneous investment growth of related firms. When related firms are experiencing contemporaneous relative growth (contraction) in their respective asset base, the negative relation between inventory growth and future firm performance for the upstream firm is much weaker (stronger). Specifically, consistent with past research, we find that the inventory growth component of earnings is less persistent than the cash flow component for our full sample (the full sample regression coefficient on ΔINV in a standard ROA time series regression is -0.136). When we split the sample into groups based on the investment growth of related firms, we find that firms whose related firms have contemporaneous relative growth (contraction) in their respective asset base, have a corresponding regression coefficient of -0.099 (-0.153), significantly different at conventional levels. We further find that the negative relation between inventory growth and future stock returns exhibits a similar differential pattern in both cross-sectional characteristic regressions and portfolio return tests. Finally, consistent with prior research, we find that sell-side analysts are slow in incorporating the differential persistence of inventory growth information into their earnings forecasts and this is concentrated in firms where related firms are experiencing contemporaneous relative contraction in their respective asset base.

Most importantly, our finding of conditional information content in the supply chain, holds after controlling for the unconditional information content of the supply chain. Specifically, all of our empirical analysis controls for the recent performance of related firms (as measured by recent stock returns). Thus, our analysis is incremental to the previously documented results in Menzly and Ozbas (2010) and Cohen and Frazzini (2008).

In later analyses, we find that the attenuation of the negative relation between inventory growth and future firm performance is concentrated in manufacturing firms where the inventory account is more economically important. We also decompose the information content of related firms into 'peer' firms (i.e., firms in the same industry) and 'non-peer' firms (i.e., firms in different industries). We find that investment growth in 'non-peer' related firms are most relevant for the attenuation of the negative relation between inventory growth and future firm profitability, and investment growth in both 'peer' and 'non-peer' firms is relevant for the attenuation of the negative relation between inventory growth and future stock returns. Our empirical analysis is *not* simply the industry momentum effect of Moskowitz and Grinblatt (1999), as we control for the recent stock returns of related firms directly. Finally, we also show that the attenuation of the negative relation between inventory growth and future firm performance is unique to growth in related firms. When we replicate our research design using growth in unrelated industries, we find no attenuation in the negative relation between inventory growth and future firm performance.

Our framework for combining information external to the firm can be viewed as an alternative expectation model for accruals or inventory growth. Past research has tended to use information specific to the firm itself to form expectations of the expected level of accruals for a given firm. For example, the most common accrual expectation models include as independent variables measures of (i) contemporaneous sales growth, (ii) capital asset intensity, (iii) past, current and future cash flows, and (iv) contemporaneous profitability(see e.g., Jones, 1991; Dechow, Sloan and Sweeney, 1995; Dechow and Dichev, 2002; and Kothari, Leone and Wasley, 2005). By extending the set of included variables to explain current levels of accruals to incorporate information *external* to the firm itself, we offer a way to condition expectations of accruals (and inventory growth in particular) using information that is exogenous to the firm itself. This approach can readily be used to create measures of accounting quality that are, at least partially, exogenous. This is likely to be useful to the extensive literature exploring the capital market consequences of accounting quality (e.g., Francis, LaFond, Olsson and Schipper, 2005; and Core, Guay and Verdi, 2008).

Our empirical analysis is related to a recent working paper by Allen, Larson and Sloan (2012). ALS conduct a variety of tests to establish *ex post* that the negative relation between inventory growth and future firm performance is concentrated in firms where the inventory growth reverses. ALS use future knowledge of future changes in inventory and subsequent inventory write-downs to show that the negative relation between inventory and subsequent firm performance is attributable to accrual reversals. Our approach complements ALS by forming *ex ante* expectations of situations where the reversal in inventory growth is most likely to occur.

The rest of the paper is structured as follows. Section 2 describes our sample selection and research design. Section 3 presents our empirical analysis and robustness tests, and section 4 concludes.

2. Sample and research design

2.1 Identification of related firms and real investment activity of related firms

It is important that we are able to identify economically meaningful links between firms. Prior research has examined a variety of measures to identify explicit linkages between firms. Examples include (i) social network linkages that arise due to commonality in corporate boards and senior executive teams (see e.g., Levine, 1972; Dooley, 1969; Davis, 1991; and Hallock, 1997), (ii) explicit firm level customer and supplier relationships (e.g., Cohen and Frazzini, 2008), and (iii) explicit industry level customer and supplier linkages (e.g., Menzly and Ozbas, 2010).

We focus our empirical strategy on industry level linkages for several reasons. First, we are able to identify such links for all US industries for the period 1988 – 2010. Second, we are able to examine the consequences of industry linkages for all firms and are not limited solely to explicit firm level linkages as would be the case with customer-supplier linkages. Our aim is to identify information external to the firm that can help *condition* the information content of firm level inventory growth. If we limit ourselves to explicit customer-supplier relationships we will be missing a lot of potentially useful information about the investment decisions of related firms. Third, by focussing on clear economic linkages between firms we are better able to identify the investment decisions of economically related firms. If we chose to look at investment decisions of firms that share directors, we would not necessarily be capturing the information content of investment decisions by related firms, unless the director commonality also reflected economic linkages between firms.

We use the Benchmark Input-Output Surveys of the Bureau of Economic Analysis (BEA Surveys) as the basis for identification of economically linked industries. These data allow us to cleanly identify linkages across customer and supplier industries. The BEA surveys provide a detailed view into the interdependencies across industries based on the production and consumption of various good and services. The BEA Surveys are updated every 5 years and are dated with a 'look-back' so the 2007 tables which are released in 2012 relate to the years 2007-2011.

The BEA Surveys contain a variety of tabulated information. We are most interested in the MAKE and USE tables. The MAKE table is a I x C matrix populated with the dollar production of each commodity, c, by each industry, i. Thus, the sum of the rows of the MAKE table reflects the total production of commodities for each industry. The USE table is a C x I matrix populated with the dollar consumption of each commodity, c, by each industry, i. Thus, the sum of the rows of the USE table reflects the total consumption of a given commodity across all industries.

We need to make several research design choices when using the BEA Surveys. First, we need to decide on the granularity of industry definition. The BEA Surveys are provided at a detailed, summary and sector level. For the 2002 BEA Surveys the dimensionality of the MAKE and USE tables across these three levels are as follows: (i) detailed (430 industry codes), (ii) summary (133 industry codes), and (iii) sector (15 industry codes). We use the summary level BEA Surveys in our empirical analysis. Second, we need to combine some intermediary industry codes to allow mapping back to standard industry classification schema such as SIC and GICS. These are performed manually for a small number of industry codes (see Menzly and Ozbas, 2010 for details). Third, we need to combine the MAKE and USE tables to create a balanced I x I matrix reflecting the *proportional* use of commodities that are produced and then used across industries within the US economy. To do this we convert the MAKE table to reflect the proportion of a given commodity that is produced by a given industry. The dollar amounts in the cells of the $I \, x \, C$ MAKE table are therefore scaled by the respective sum of each row (i.e., the total amount of that commodity that is produced across all industries in the US economy). Likewise, we convert the USE table to reflect the proportion of a given commodity that is consumed by a given industry. The dollar amounts in the cells of the $C \, x \, I$ USE table are therefore scaled by the respective sum of each row (i.e., the total amount of that commodity that is consumed across all industries in the US economy). We then take the matrix multiplication across the modified MAKE and USE tables to create an $I \, x \, I$ industry level input-output table.

Appendix I shows the final input-output table for the sector level (15 industry codes) using the 2002 BEA Survey tables. For example, the agriculture, forestry, fishing and hunting sector (labelled as AGRIC) consumes 31 percent of the commodities that it produces and the bulk of the rest is consumed by the manufacturing sector (labelled as MANUF). It is clear from this visualization that there is a concentration of economic activity along the main diagonal. Thus, our input-output matrix reflects the combined effect of related firms in the same industry and related firms that operate in different industries. Not surprisingly, there is a strong within industry economic interdependence between firms in the US economy. In our later empirical analysis we separately examine the two types of related firms.

We assign all firms to the industry classification schema used as the basis of our summary level industry input-output table. To measure the real investment activity of related firms, we first compute the change in net operating assets, ΔNOA, for all firms in each industry. We measure ΔNOA as in Richardson, Sloan, Soliman and Tuna (2005). We aggregate ΔNOA across all firms in a given industry. Results are similar using equal or value weighting, and our tabulated results use value weighted measures. Our selection of growth in net operating assets is to reflect the totality of real investment decisions, and not just focussing on one portion of the balance sheet. To estimate the real investment activity of related firms, we use the weights implied by the *I x I* industry level input-output table. For example, using the sector input-output table described in Appendix I, firms in the agriculture, forestry, fishing and hunting sector are assigned a measure of real investment activity of related firms based on (i) 31% of the real investment activity of other agriculture, forestry, fishing and hunting firms, (ii) 62.7% of the real investment activity of firms in the manufacturing sector, and (iii) the remaining 6.3% attributable to the real investment activity of firms in the other industries with non-zero cells in the top row of the matrix in Appendix I. Thus, for each industry we compute the sum-product of the respective row in the input-output table and the vector of ΔNOA averages for each industry. The resulting industry level measures are then used to sort firms into groups (terciles for our primary empirical analysis) based on the real investment activity of related firms.

2.2 Our empirical tests

We conduct three sets of empirical analyses. First, we assess whether real investment decisions of related firms attenuates the negative relation between inventory growth and future firm profitability. Second, we assess whether real investment decisions of related firms attenuates the negative relation between inventory growth and future stock returns. Third, we assess whether sell-side analysts efficiently *combine* knowledge of inventory growth of the firm they are forecasting with investment growth of related firms. A benefit of these analyst revision tests is that, under the assumption that analyst forecasts are representative of the earnings expectations of the marginal investor, documenting systematic relations in sell-side analyst earnings expectations errors, makes it harder to attribute the negative relation between inventory growth and future stock returns to a risk based explanation (e.g., Bradshaw, Richardson and Sloan, 2001).

All of the fundamental data used to compute the measures described in the following sub-section are derived from interim financial statements collected by Compustat. Analyst forecast data are sourced from I/B/E/S. Our market data are obtained from CRSP. Our tabulated analyses are based on trimming the top and bottom 2 percent of observations of variables (with the exception of stock returns and firm size) each month (quarter) to minimize the influence of outliers. Results are unaffected by instead using a 1 percent trimming rule. We include all firms in our analysis with non-missing data to compute measures of inventory growth and exclude financial firms (SIC between 6000 and 6999) as is standard in this literature.

2.2.1 Firm fundamentals

Our first empirical prediction can be stated in alternative form as:

P1: Real investment decisions of related firms are useful to condition expectations for the negative relation between inventory growth and future firm profitability.

We test this by examining whether the negative relation between inventory growth, ΔINV, and future firm profitability, ROA, differs across groups sorted on the basis of real investment growth of related firms. We use a standard benchmark forecasting model for firm level profitability which acknowledges profitability is mean reverting and also exploits various firm characteristics that isolate differences in persistence of profitability (see e.g., Fama and French, 2000; and Hou, van Dijk and Zhang, 2012). Specifically, we run the following regression for each quarter (firm subscripts, *i*, dropped for the sake of brevity):

$$ROA_{t+1} = \alpha + \beta_1 ROA_t + \beta_2 \Delta INV_t + \beta_3 BTM_t + \beta_4 Size_t + \beta_5 D\_Loss_t + \beta_6 D\_Yield_t + \beta_7 RET_t^{RELATED} + e_{t+1} \qquad (1)$$

ROA_t is return on assets for the previous twelve months, calculated as income before extraordinary items divided by average total assets. BTM_t is book-to-price measured as the book value of common equity divided by market capitalization using data available at the start of the period for which we examine future profitability, $Size_t$ is the log of market capitalization, D_Loss_t is an indicator variable equal to one for firms reporting a loss in year *t*, and zero otherwise, Div_Yield_t is the dividend yield for year t, and $RET_t^{RELATED}$ is the average recent (6 month) stock returns of all related firms. We estimate this regression for the pooled sample and report standard errors clustering for both time and firm dependencies. We expect profitability to be mean reverting so our priors are for β_1 to be less than one and greater than zero. We expect firms with greater growth opportunities, as measured (inversely) by BTM_t , to have high levels of profitability after controlling for current profitability, so we expect a negative β_3 coefficient. We also expect smaller firms to exhibit lower levels of future profitability controlling for current profitability, so we expect a positive β_4 coefficient. We expect loss making firms to have lower profitability (i.e., $\beta_5 < 0$) and firms paying dividends to have higher profitability (i.e., $\beta_6 > 0$). We expect to find a strong unconditional relation between the performance of related firms along the supply chain (i.e., $\beta_7 > 0$). Finally, we expect a negative coefficient for our primary variable of interest, ΔINV_t, but we expect this negative relation to vary across groups formed on the basis of $\Delta NOA_t^{RELATED}$. Specifically, we expect β_2 to become less negative as we move from firms where related firms have relative contractions in real investment activity (i.e.,$\Delta NOA_t^{RELATED}$ is low) to firms where related firms have relative expansion in real investment activity (i.e., $\Delta NOA_t^{RELATED}$ is high).

2.2.2 Stock returns

Our empirical prediction can be stated in alternative form as:

P2: Stock prices do not efficiently incorporate information on real investment decisions of related firms.

We employ standard cross-sectional characteristic regressions and time series portfolio tests to assess the relation between future stock returns and inventory growth across groups of firms formed on the basis of real investment activity in related firms.

For our cross sectional characteristic tests, we run the following regression every month (again firm subscripts, i, dropped for the sake of brevity):

$$RET_{t+k} = \alpha + \beta_1 RET_t + \beta_2 \Delta INV_t + \beta_3 BTM_t + \beta_4 {}^{NI}/_{P_t} + \beta_5 Beta_t + \beta_6 Size_t$$
$$+ \beta_7 Momentum_t + \beta_8 D\_Loss_t + \beta_9 RET_t^{RELATED} + e_{t+k} \qquad (2)$$

Equation (2) is estimated for the next three months (i.e., k = 1 to 3). To simplify the interpretation of the results, we examine each month separately (i.e., the stock returns, RET_{t+k}, are not cumulated across K months, but instead focus on the Kth month). The relevant test is whether $\beta_2 = 0$, and finding $\beta_2 < 0$ is consistent with stock returns failing to efficiently incorporate information about inventory growth in a timely manner. We are most interested in whether the magnitude of β_2 diminishes as we move from firms where related firms have relative contractions in real investment activity (i.e., $\Delta NOA_t^{RELATED}$ is low) to firms where related firms have relative expansion in real investment activity (i.e., $\Delta NOA_t^{RELATED}$ is high). Consistent with prior research, we include firm characteristics known to be associated with future returns: NI/P_t and BTM_t (e.g., Fama and French, 1992 and 2008). BTM_t is as defined previously. NI/P_t is computed as net income before extraordinary items across the last four quarters divided by market capitalization as at the end of the most recent fiscal quarter. We expect both β_3 and β_4 to be positively associated with future returns. We also include measures of firm size, $Size_t$, as defined earlier, and $Beta_t$, measured as the single factor CAPM beta, using monthly data from the last 60 months for each security (minimum of 24 months required); we expect β_5 to be positive and β_6 to be negative. We also include two measures of recent stock returns. The first measure is RET_t, which is the return for the most recent month. Given prior research has documented a short term reversal effect (e.g., Jegadeesh, 1990) we expect β_1 to be negative. The second measure is $Momentum_t$, is the most recent six month cumulative return dropping the most recent month. As prior research has shown a continuation in stock returns over the medium term, we expect β_7 to be positive. We also include an indicator for loss making firms, D_Loss_t, and $RET_t^{RELATED}$ as defined previously to capture the unconditional information content of related firm performance (we expect β_9 to be positive). We estimate equation (2) using size weighted cross sectional regressions.

For our portfolio level analyses we sort firms into groups based on $\Delta NOA_t^{RELATED}$ and then within each group we sort firms into groups based on ΔINV_t. This allows us to assess the differential return performance of portfolios of firms formed on the basis of their own inventory growth *across* groups of firms formed on the basis of real investment growth of related firms. We examine both total returns and characteristic adjusted returns (Daniel, Grinblatt, Titman and Wermers, 1997) across the resulting portfolios. In addition we also report 'alphas' from time series regressions, where we regress portfolio monthly excess returns (over the return on the U.S. one-month Treasury bill) on (i) excess returns associated with market, MKT, (ii) factor mimicking portfolio returns associated with size, SMB, (iii) factor mimicking portfolio returns associated with book-to-price, HML, and (iv) factor mimicking portfolio returns associated with momentum, UMD. The factor returns for MKT, SMB, HML and UMD and the one-month Treasury return were obtained from Kenneth French's website at:

http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html.

2.2.3 Sell-side analyst earnings forecasts

Prior literature has shown that analyst forecasts appear to be slow in incorporating a variety of information (e.g., Bradshaw, Richardson and Sloan, 2001 and 2006 for measures of accruals and external financing). We revisit the strength of this relation based on the real investment activity of related firms. Therefore, our final empirical prediction can be stated in alternative form as:

P3: Sell-side analysts do not efficiently incorporate information on real investment decisions of related firms into their earnings forecasts.

We test P3 directly by examining the speed with which analysts incorporate the information contained in ΔINV_t into their firm level earnings forecasts across groups of firms formed on the basis of $\Delta NOA_t^{RELATED}$. Specifically, we estimate the following regression every month (again firm subscripts, i, dropped for the sake of brevity):

$$Revision_{t+k} = \alpha + \beta_1 Revision_t + \beta_2 \Delta INV_t + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Momentum_t + \beta_6 D\_Loss_t + \beta_7 RET_t^{RELATED} + e_{t+k} \quad (3)$$

Equation (4) is estimated for the next three months (i.e., k = 1 to 3). $Revision_t$ is the monthly revision in consensus sell-side analyst forecasts. To ensure cross-sectional comparability of sell-side analyst earnings forecasts across firms with different fiscal year ends, we first take a calendar weighted average of one year ahead, $E[EPS1Y_t]$, and two-year ahead earnings forecasts,$E[EPS2Y_t]$, where the weight is a linear function of the number of months to the end of the next fiscal year. We label the resulting twelve month ahead forecast: $E[EPS12M_t]$. For example, in March 2010 for a December year end firm we place

9/12 weight on the forecast for the 2010 fiscal year and 3/12 weight on the forecast for the 2011 fiscal year. The consequence of this choice is that our resulting earnings forecast is twelve months ahead for all firms. Finally, we compute $Revision_t$ as:

$$Revision_t = ln\frac{E[EPS12M_t]}{E[EPS12M_{t-1}]} \qquad (4)$$

Given that we use the natural logarithm operator we restrict our firms to those where the calendar weighted forecasts across both months are strictly positive, but our results are not sensitive to computing an alternative revision measure which retains negative forecasts. Prior literature has shown that analyst forecast revisions are highly serially correlated (e.g., Hughes, Liu and Su, 2008). We therefore expect β_1 to be positive. BTM_t and NI/P_t are as defined previously. We expect both β_3 and β_4 to be negative, as firms with high expectations of earnings growth should, on average, deliver that earnings growth (and changing expectations of growth). $Momentum_t$ is as defined previously. We include this variable as prior research has shown that sell side analyst forecasts reflect expectations embedded in stock price with a lag (e.g., Hughes, Liu and Su, 2008), and hence we expect β_5 to be positive. We also include an indicator for loss making firms, D_Loss_t, and $RET_t^{RELATED}$ as defined previously to capture the unconditional information content of related firm performance (we expect β_7 to be positive). Finally, we expect β_2 to be negative for our full sample estimation (Bradshaw, Richardson and Sloan, 2001), and we expect this negative relation to diminish as we move from firms where related firms have relative contractions in real investment activity (i.e., $\Delta NOA_t^{RELATED}$ is low) to firms where related firms have relative expansion in real investment activity (i.e., $\Delta NOA_t^{RELATED}$ is high).

3. Results

3.1 Firm fundamentals

Panel A of table 1 provides the breakdown of our sample firms across the industry groupings identified from the summary level BEA Surveys. For each industry we report distributional information about $\Delta NOA^{RELATED}$, our measure of real investment activity in related firms. There are on average 125 industry groupings reflected in the summary level BEA data tables over the time period we examine, and for the sake of brevity we report this information only for the 30 most populated industry groupings. The 30 industry groupings we report in table 1 capture 93 percent of the total 555,696 firm-months that are in our full sample. We see considerable variation in the real investment activity of related firms across each industry grouping *and* through time. This is a necessary condition for our research design to have any power. For example, over the 1988-2010 sample period, the related industries that do business with the computer and data processing service firms experienced average annual growth in net operating assets equal to 7.03 percent of average assets. Further, this rate of growth in real investment activity varied from 6.03 percent (lower quartile) to 8.74 percent (upper quartile) over theses 23 years. In contrast, over the 1988-2010 sample period, the related industries that do business with the audio, video and communications equipment manufacturing firms experienced average annual growth in net operating assets equal to -0.37 percent of average assets, with a lower (upper) quartile of -4.71 (2.91) percent. Clearly, there is considerable variation in the real investment activities of related firms, and it is this variation we will exploit to condition the negative relation between firm specific inventory growth and future firm performance.

Panel B of table 1 reports distributional information for the firm characteristics used in estimation regression equations (1), (2) and (3). The average firm in our sample has (i) monthly total returns of 1.3 percent, (ii) inventory growth of 1.4 percent of average total assets, (iii) profitability of 1.8 percent of average total assets, (iv) a book-to-price ratio of 0.62, and (v) an earnings-to-price ratio of -0.05 (limiting to profit only firms the average earnings-to-price ratio is 0.06). 36 percent of our sample firms report losses, and the dividend yield is 0.6 percent for the average firm.

Table 2 reports the regression coefficient estimates of equation (1). We estimate this regression using 187,397 pooled firm-quarter observations. To control for dependence in the pooled sample we cluster our standard errors across both firms and quarters. We estimate equation (1) for all firms together and then separately for three equal sized groups based on the real investment activity of related firms. For the full sample we find results consistent with prior research: (i) profitability is mean reverting as evidenced by the β_1 coefficient of 0.669, (ii) the level of future profitability is decreasing (increasing) in BTM and ($Size$), (iii) future profitability is lower (higher) for loss making (dividend paying) firms, and (iv) future profitability is related to the performance (as measured by stock returns) of related firms. All of these results are consistent with recent research (e.g., Hou, van Dijk and Zhang, 2012 and Menzly and Ozbas, 2010). We also find a strong negative relation between inventory growth and future profitability, consistent with prior work on 'accruals' (e.g., Sloan, 1996).

When we estimate equation (1) across groups of firms based on the real investment activity of related firms, we find similar associations between the various explanatory variables and future profitability. Consistent with P1 we find the negative association between inventory growth and future profitability varies monotonically across the three groups. Specifically, we find that inventory growth is less negatively associated with future profitability for firms in industries where related firms are also experiencing real investment growth. We strongly reject the null hypothesis that the association between inventory growth and future profitability does not vary across the three groups (test statistic of 3.25 significant at better than the 1 percent level). This suggests that the negative relation between inventory growth and future profitability is partially explained by sub-optimal investment decisions, particularly for firms that grow their inventory when related firms are not experiencing real investment growth.

3.2 Stock returns

Table 3 reports our estimation of equation (2). We estimate this regression using 555,696 firm-month observations. As is standard in cross-sectional asset pricing tests we estimate this regression every month and use the time series of regression coefficients to construct test-statistics. Equation (1) is estimated fort the next three months. For the full sample we find consistent with prior research that future stock returns are (i) negatively correlated with the most recent stock returns, the 'reversal' effect, (ii) negatively associated with ΔINV, (iii) positively associated with BTM and NI/P, (iv) weakly positively associated with $Beta$, (v) negatively related with $Size$, (vi) weakly associated with $Momentum$ (our sample period includes the recent 'crash' associated with momentum, Daniel and Moskowitz, 2012), (vii) weakly negatively associated with loss making status, and (viii) positively associated with the recent performance of related firms.

When we estimate equation (2) across groups of firms based on the real investment activity of related firms, we find similar associations between the various explanatory variables and future stock returns. Consistent with P2 we find the negative association between inventory growth and future stock returns decreases monotonically as we move from the LOW to HIGH group. Specifically, we find that inventory growth is less negatively associated with future stock returns for firms in industries where related firms are also experiencing real investment growth. We can therefore strongly reject the null hypothesis that the association between inventory growth and future stock returns does not vary across the three groups (test statistic of 2.65 significant at better than the 1 percent level for one month ahead stock returns).

To visualize the significance of the difference in the strength of the negative relation between inventory growth and future stock returns we sort firms into quartiles each month based on inventory growth over the most recent four fiscal quarters. We do this sort separately for groups of firms based on the real investment activity of related firms. We then compute a hedge portfolio return as the difference between the long return for the lowest quartile of inventory growth and the short return for the highest quartile of inventory growth and cumulate these monthly portfolio returns. The cumulated portfolio returns are shown in Figure 1. The bold (dashed) line plots these portfolio returns within the top (bottom) group based on real investment growth in related firms. There is a striking difference in the strength of the negative relation between inventory growth and future stock returns across these two groups. The Sharpe ratio is 1.23 (0.51) for the LOW (HIGH) groups respectively. To test the relative attractiveness across these two series of portfolio returns we conduct standard asset pricing tests to determine optimal portfolio weights in a mean-variant framework (e.g., Britten-Jones, 1999). This test simply regresses a vector of 1s against the time series of the relevant asset (i.e., portfolio) returns and the coefficients from the regression provide the optimal in-sample weight to achieve the best (i.e., closest to an arbitrage opportunity) returns for an investor. This test reveals a striking difference across portfolios that take long (short) positions in low (high) inventory growth firms. The optimal weight on the long-short inventory growth portfolio for the set of firms with LOW investment growth in related firms is 78% and the optimal weight on the long-short inventory growth portfolio for the set of firms with HIGH investment growth in related firms is 22% (these portfolio weights are statistically different at the one percent level). Inferences are virtually identical if we use characteristic adjusted returns (e.g., Daniel, Grinblatt, Titman and Wermers, 1997) instead of total returns when computing the portfolio returns.

To help assess the robustness of the results to the linearity assumption underlying our regression analysis reported in table 3, we also document the relation across portfolios formed on the joint sort of $\Delta NOA^{RELATED}$ and ΔINV. Specifically, each month we first sort all firms into four equal sized groups based on real investment activity in related firms (i.e., $\Delta NOA^{RELATED}$) and then within each $\Delta NOA^{RELATED}$ quartile, we further sort firms into four equal sized groups based on firm specific inventory growth (i.e., ΔINV). Panel A of table 4 reports the inventory growth across the resulting 16 equally populated cells. Across each column we see a similar spread in ΔINV across the four $\Delta NOA^{RELATED}$ quartiles: across all four groupings the difference in inventory growth is about 11.5 percent of average total assets. Similarly, in panel B of table 4 we report the real investment activity across the 16 equally populated cells. Across each row in this panel we see a similar spread in $\Delta NOA^{RELATED}$ across the four ΔINV quartiles: across all four groupings the difference in real investment activity is about 6.75 percent of average total assets. The purpose of the first two panels in table 4 is to show that the differences we document between ΔINV and future stock returns across $\Delta NOA^{RELATED}$ groupings is not attributable to differences in either the scale or dispersion of the sorting variables.

Panel D (E) of table 4 reports the total (characteristics adjusted) monthly return across the 16 cells. We see strong evidence of the negative relation between ΔINV and future stock returns for each $\Delta NOA^{RELATED}$ grouping. For example, the monthly difference in total returns for firms across the extreme quartiles of inventory growth is -1.23 (-0.71) percent for the lowest (highest) $\Delta NOA^{RELATED}$ grouping, with both differences significant at conventional levels. Consistent with the regression results report in table 3, we also find a significant difference in the relation between ΔINV and future stock returns across the extreme $\Delta NOA^{RELATED}$ groupings. Specifically, the difference in the HI-LO returns is 0.52 (0.53) percent per month for total returns (characteristic adjusted returns), again significant at conventional levels. Finally, in panel E of table 4 we report the intercepts from time-series regressions where we regress portfolio monthly excess returns (over the return on the U.S. one-month Treasury bill) on (i) excess returns associated with market, MKT, (ii) factor mimicking portfolio returns associated with size, SMB, (iii) factor mimicking portfolio returns associated with book-to-price, HML, and (iv) factor mimicking portfolio returns associated with momentum, UMD. We again see significant negative relation between ΔINV and future 'alphas' across $\Delta NOA^{RELATED}$ groupings, and the difference in 'alpha' across the extreme $\Delta NOA^{RELATED}$ groupings is 0.44 percent per month significantly different from zero at the ten percent level.

Across the analyses reported in tables 3 and 4, we find evidence consistent with P2 that stock prices do not appear to efficiently incorporate information in real investment decisions of related firms. Of course, this inference is conditional on our ability to appropriately measure expected returns (e.g., Fama, 1998). However, a benefit of conditioning the return relation based on information that is external (and arguably exogenous) to the firm itself, is that any risk based explanation for the relation between ΔINV and future returns must also be able to explain why the risk inherent in inventory growth varies as a function of the real investment activity of related firms. A more natural interpretation of the attenuation in the negative relation between ΔINV

and future stock returns across $\Delta NOA^{RELATED}$ groupings, is that the real investment activity of related firms helps isolate sub-optimal investment decisions of firms, especially for firms that are growing their inventory base when related firms are (relatively) contracting their real investment activities. This relation is evident in both the fundamental analysis reported in table 2 as well as the stock return analyses reported in tables 3 and 4.

3.3 Analyst revisions

Table 5 reports our estimation of regression equation (4). For this analysis we have a smaller sample due to the requirement of sell-side earnings forecasts collated by I/B/E/S. Our full sample comprises 268,736 firm-months, with equation (1) estimated each month, regression coefficients averaged across months, and standard errors based on the time series variation in the monthly regression coefficients. For the full sample we see that analyst revisions are (i) strongly serially correlated (the β_1 coefficient is 0.218 indicating that 21 percent of the revision carries over to the next month), (ii) positively related to market expectations for growth (the β_3 and β_4 coefficients are significant for the one month ahead specification, and β_4 is significant for the following three months), (iii) strongly related to past returns (the β_5 coefficient is significant for the following three months), (iv) positively associated with past loss making occurrence suggesting that analysts are initially too pessimistic for loss making firms, and (v) positively associated with recent performance of related firms (the β_7 coefficient is strongly positive consistent with Menzly and Ozbas, 2010). Finally, consistent with Bradshaw, Richardson and Sloan (2001) we find a robust negative relation between ΔINV and future analyst revisions, consistent with analyst failing to incorporate the information content of inventory growth in a timely manner.

When we estimate equation (4) across groups of firms based on the real investment activity of related firms, we find similar associations between the various explanatory variables and future analyst earnings revisions. Consistent with P2, we find the negative association between inventory growth and future analyst revisions decreases monotonically as we move from the LOW to HIGH group. Specifically, we find that inventory growth is *not* associated with future analyst revisions for firms in industries where related firms are also experiencing real investment growth. Thus, for the sample of firms where inventory growth has a weaker association with future profitability and future stock returns (HIGH group) there is no systematic evidence of analyst optimism related to the level of 'accruals'. However, for the sample of firms where inventory growth has a strong negative relation with both future profitability and future stock returns (LOW group) we find strong evidence of analyst optimism varying with the level of 'accruals'. We can reject the null hypothesis that the association between inventory growth and future analyst revisions does not vary across the two groups (test statistic of 2.21 significant at better than the 1 percent level for one month ahead analyst earnings revisions).

The results in table 5 are consistent with P3 that sell-side analysts do not efficiently incorporate information on real investment decisions of related firms into their earnings forecasts, primarily for the set of firms growing their inventory base when there is no real investment activity in related firms. As noted earlier, an additional benefit of the analyst revision tests is that, under the assumption that analyst earnings forecasts are representative of the earnings expectations of the marginal investor, documenting systematic relations in sell-side analyst earnings expectations errors, suggests that the relation between ΔINV and future stock returns is attributable to errors in expectations on future cash flows and not attributable to a risk based explanation.

3.4 Extensions

3.4.1 Limiting sample to manufacturing firms

Given that our focus is on inventory growth it is natural to examine a subset of firms where inventory is an economically meaningful asset. Consistent with past research (e.g., Roychowdhury, 2006) we classify all firms belonging to two-digit SIC codes between 20 and 39 as manufacturing firms. For this reduced sample we re-estimate regression equations (1), (2) and (4). Table 6 reports the results.

Panel A of table 6 reports the estimation of equation (1) for the sample of 109,301 manufacturing firm-quarters. We see very similar relations as before for the full sample and continue to see a monotonic relation between ΔINV and future profitability across $\Delta NOA^{RELATED}$ groupings. As before we can reject the null hypothesis that the association between inventory growth and future profitability does not vary across the three groups (test statistic of 2.10 significant at better than the 1 percent level).

Panel B of table 6 reports the estimation of equation (2) for the sample of 324,768 manufacturing firm-months. The regression estimate for the full sample looks very similar to that reported in table 3 (we only report one month ahead stock return analysis for the sake of brevity). We continue to see a monotonic relation between ΔINV and future stock returns across $\Delta NOA^{RELATED}$ groupings (the difference in the β_2 regression coefficient of -0.070 [-0.034] for the low [high] $\Delta NOA^{RELATED}$ group is significant with a test-statistic of 2.17).

Finally, panel C of table 6 reports the estimation of equation (4) for the sample of 150,144 manufacturing firm-months. The regression estimate for the full sample looks very similar to that reported in table 5 (we only report one month ahead stock return analysis for the sake of brevity). While we continue to see a monotonic relation between ΔINV and future analyst earnings revisions across $\Delta NOA^{RELATED}$ groupings we only find modest statistical evidence of a difference (the difference in the β_2 regression coefficient of -0.023 [-0.004] for the low [high] $\Delta NOA^{RELATED}$ group has a test-statistic of 1.41).

3.4.2 Splitting PEER and NON-PEER firms

Our tabulated empirical analysis includes two types of related firms: (i) related firms in the same industry, and (ii) related firms along the supply chain. For our primary hypotheses, we are interested in conditioning the negative relation between inventory growth and future firm performance at the firm level via utilizing information on the real investment activity of *all* related firms. However, the interested reader may be interested in knowing whether it is the real investment activity of related firms in the same industry or the real investment activity of related firms in different industries that drive the empirical results.

To address this issue we re-estimate regression equations (1) and (2) splitting each cross-section into three equal size groups based on the real investment activity of (i) only related firms in the same industry, and (ii) only related firms in different industries. Thus, we have two sets of cross-sectional partitions every quarter (month) when estimating the fundamental (stock returns and analyst earnings revisions) tests. These cross-sectional partitions are simply additively decomposing the industry level input-output table into the diagonal components (same industry) and off-diagonal components (different industries). The diagonal (off-diagonal) components of our industry level input-output table account for on average 18 (82) percent of industry output. Thus, the majority of the industry level linkages are due to the industry supply chain *across* industries.

In unreported analyses, we find that the attenuation of the negative relation between ΔINV and future profitability across $\Delta NOA^{RELATED}$ groups is attributable to the real investment activity of related firms in different industries. We find that the β_2 coefficient when estimating equation (1) for the low (high) $\Delta NOA^{RELATED}$ groupings based on firms in different industries is -0.158 (-0.079) with the difference significant at conventional levels (test statistic of 4.32). In contrast, we are unable to reject the null hypothesis of a difference in the β_2 coefficient across $\Delta NOA^{RELATED}$ groupings based on firms in the same industry.

Estimation of equation (2) also provides similar results. We find the attenuation in the negative relation between ΔINV and future stock returns across $\Delta NOA^{RELATED}$ groups based for both within and across industry groupings. The strength of this attenuation is, however, weaker for the across industry grouping as we can only reject the difference at the ten percent level.

3.4.3 Rescaling USE and MAKE tables to allow scale for each industry to sum to less than one

Our empirical analysis is based on several choices in converting the MAKE and USE tables of the BEA into an industry level input-output table. One of the choices that we made was to force both the MAKE and USE table to have rows sum to one (i.e., we forced the total commodity production for each industry to sum to 100 percent, *and* we forced the total commodity usage for each industry to sum to 100 percent). The BEA MAKE and USE tables include government and related categories which we do not consider in our analysis (such categories do not contain firms). However, this choice could lead to inconsistent treatment in the economic importance in the links across industries. For example, a given commodity may ultimately be primarily used by the government and our choice to force the usage to sum to 100 percent could artificially increase the scale of input-output links for government facing industries.

To address this issue we have instead allowed the rows of the MAKE and USE table to sum to less than 100 percent and thereby preserve the natural scale of the economic importance across industries. Our results are virtually identical from this analysis (for the sake of brevity, these results available on request).

3.4.4 Alternative groupings

Our reported analyses are based on partitions of firms into three (or four) equal sized groups. We have repeated all of our analysis using quintile and decile groupings and find very similar results (again for the sake of brevity, these results available on request). We have chosen three groupings as our primary focus to maximize the trade-off between power in sample sizes and variation across the resulting groups (see e.g., Lys and Sabino, 1992).

3.4.5 Exploiting industries that vary real investment activity through time

A potential criticism of our empirical design is that we are simply identifying industries for which the negative relation between inventory growth and future firm performance is less strong. To address this criticism we first note that this explanation is unlikely as we are sorting firms each quarter (fundamental tests) and each month (return and revision tests). It is true that the BEA Survey tables that we use to construct our industry input-output tables are only updated every 5 years and are likely to be stable through time. However, the real investment activity of economically related firms can and does change through time.

To address this issue more directly we classify each industry into groups based on the consistency with which they are classified as having 'LOW' or 'HIGH' real investment activity. We then repeat all of our empirical analysis separately for industries that are more consistently classified as ‘LOW’ or ‘HIGH’ through time and those industries that are more varied in this classification. We find that the relation between inventory growth and future firm performance is actually stronger for industries which more consistently experienced low or high levels of real investment growth. Thus, the stickiness of real investment activity across industry groups cannot explain our results.

3.4.6 Is the effect attributable to ‘growth’ in general?

Our research design seeks to exploit cross-sectional variation in the growth of related industries. A potential concern with this approach is that growth in related industries could be correlated with growth in the broader economy. While we have no reason to expect this ex ante, we have repeated all of our empirical analysis by instead sorting firms into three groups based on real investment activity in *unrelated* firms. Specifically, we reconstruct the industry input-output matrix by (i) assigning a value of ‘0’ to all cells in the original industry input-output matrix that had a non-zero value, and (ii) assigning a value of ‘1’ to all cells in the original industry input-output matrix that had a zero value. In effect, we equally weight our measure of real investment activity (i.e., ΔNOA) across all unrelated industries for each industry. We then repeat all of our empirical analyses partitioning firms into three equal sized groups each cross-section using the resulting $\Delta NOA_t^{UNRELATED}$ measure. Across all of tests (future profitability, future analyst revisions and future stock returns) we find no evidence of attenuation in the negative relation between ΔINV and future firm performance across the respective $\Delta NOA^{UNRELATED}$ groups. It is only when there is growth in real investment activity of economically related firms do we see an attenuation in the negative relation between ΔINV and future firm performance.

4. Conclusion

In this paper we use information external to the firm to condition forecasts of future firm performance. Starting with the well-known negative relation between inventory growth and future firm performance, we find that the strength of this relation is greatly attenuated when related firms are also engaging in contemporaneous real investment activity.

For a sample of 555,696 US firm-months over the 1988-2010 period, we find that knowledge of real investment decisions in related firms helps condition the negative relation between inventory growth and future firm performance. We use industry level MAKE and USE tables from the BEA to construct an industry level input-output linkage table. When firms in related industries as identified by this input-output table experience contemporaneous relative growth (contraction) in their respective asset base, the negative relation between inventory growth and future firm performance for the firm is much weaker (stronger).

Our approach of conditioning relations between firm attributes and future outcome variables using information external to the firm has several attractions that are likely to make this approach of interest to other researchers. First, a benefit of conditioning the relation inventory growth and future stock returns based on information that is external (and arguably exogenous) to the firm itself, is that any risk based explanation for the relation must also be able to explain why the risk inherent in inventory growth varies as a function of the real investment activity of related firms. Second, the conditioning offers a potentially exogenous measure of accounting quality. The current measures of accounting quality in the literature rely on firm specific measures to determine expected levels of 'accruals'. Again, by utilizing information external to the firm it is possible to identify potentially exogenous determinants of accounting quality choices that can then be linked to other outcome variables such as cost of capital.

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Appendix I: Visualization of the 2002 Sector level input-output table

	AGRIC.	MINES	UTIL	CONSTR.	MANUF.	WSALE	RETAIL	TRANS.	INFO	FIN	BUS SRVC	SOCIAL	ARTS	OTH SRVC.	GOVT
AGRIC.	0.310	0.002	0.000	0.012	0.627	0.001	0.008	0.000	0.000	0.007	0.004	0.002	0.018	0.001	0.008
MINES	0.004	0.035	0.243	0.042	0.600	0.002	0.003	0.007	0.003	0.008	0.004	0.005	0.004	0.002	0.038
UTIL	0.029	0.025	0.002	0.020	0.321	0.025	0.066	0.020	0.023	0.097	0.043	0.082	0.077	0.025	0.144
CONSTR.	0.008	0.043	0.047	0.004	0.080	0.007	0.020	0.029	0.035	0.364	0.033	0.017	0.018	0.017	0.277
MANUF.	0.017	0.007	0.004	0.096	0.551	0.018	0.026	0.027	0.023	0.025	0.030	0.047	0.032	0.015	0.084
WSALE	0.026	0.007	0.004	0.071	0.483	0.072	0.040	0.023	0.020	0.043	0.029	0.051	0.035	0.016	0.080
RETAIL	0.004	0.005	0.002	0.507	0.116	0.014	0.032	0.030	0.009	0.115	0.027	0.034	0.028	0.056	0.021
TRANS.	0.018	0.010	0.059	0.044	0.233	0.075	0.076	0.181	0.033	0.039	0.063	0.028	0.021	0.019	0.101
INFO	0.001	0.004	0.004	0.027	0.107	0.029	0.034	0.020	0.291	0.085	0.143	0.053	0.027	0.025	0.151
FIN	0.019	0.015	0.006	0.022	0.058	0.028	0.060	0.031	0.033	0.422	0.094	0.089	0.035	0.046	0.042
BUS SRVC	0.002	0.012	0.008	0.046	0.204	0.054	0.049	0.031	0.061	0.112	0.153	0.067	0.043	0.023	0.134
SOCIAL	0.022	0.000	0.003	0.005	0.004	0.010	0.044	0.002	0.010	0.005	0.013	0.451	0.010	0.037	0.384
ARTS	0.002	0.002	0.020	0.022	0.090	0.024	0.030	0.028	0.101	0.133	0.217	0.073	0.101	0.034	0.123
OTH SRVC.	0.007	0.002	0.004	0.091	0.119	0.040	0.044	0.034	0.048	0.163	0.130	0.077	0.048	0.036	0.156
GOVT	0.004	0.002	0.005	0.004	0.046	0.085	0.085	0.149	0.047	0.088	0.080	0.126	0.091	0.033	0.155

Appendix I: The final input-output table for the sector level (15 industry codes) using the 2002 Bureau of Economic Analysis Survey tables. To create this sector level input-output table we first transform the respective *MAKE* and *USE* tables to create a balanced matrix reflecting how the total set of commodities are produced and utilized across the US economy. Details can be found in section 2.1.

Appendix II: Variable definitions

Variable	Description
$Beta$	Equity market beta estimated from a rolling regression of 60 months of data requiring at least 24 months of non-missing return data.
BTM	Book-to-market ratio computed as the ratio of common equity to equity market capitalization, both measured at the fiscal period end date for the most recent *and* available fiscal quarter prior to month *t*.
D_Yield	Dividends per share divided by the stock price.
D_Loss	An indicator variable equal to one for firms that have negative earnings before extraordinary items and zero otherwise.
ΔInv	The change of total inventories over the previous twelve months scaled by average total assets.
$\Delta NOA^{RELATED}$	The change of net operating assets of the related firms over the previous twelve months, scaled by average total assets, where net operating assets are calculated as operating assets (total assets less the sum of cash and investments) minus operating liabilities (total liability minus total debt).
HML	Monthly return to the value factor, obtained from Ken French's website.
MKT	Monthly excess (to risk free rate) market return, obtained from Ken French's website.
MOM	Monthly return to the momentum factor, obtained from Ken French's website.
$Momentum$	The average monthly equity return inclusive of dividends from month *t-6* to month *t-1*.
NI/P	Earnings-to-Price ratio computed (i) for positive income firms as the ratio of net income before extraordinary items for the previous twelve months to equity market capitalization, both measured at the fiscal period end date for the most recent *and* available fiscal quarter prior to month *t*, and (ii) for loss firm it is set equal to zero.
RET	Monthly equity return inclusive of dividends.
$RET^{RELATED}$	The average size weighted monthly equity return inclusive of dividends from month *t-6* to month *t* of the related firms.
ROA	Return on assets computed as the ratio of net income before extraordinary items for the previous twelve months to average total assets.
$Revision$	This is the monthly revision in median consensus sell-side analyst earnings forecasts. Earnings forecast revision is calculated as $Revision_{i,t+k} = \ln \frac{E[EPS12M_{i,t+k}]}{E[EPS12M_{i,t+k-1}]}$, where $E[EPS12M_{i,t}]$ is a calendar weighted combination of one year ahead, $E[EPS1_{i,t}]$, and two year ahead, $E[EPS2_{i,t}]$, earnings forecasts as at month *t*. The weights across the two earnings forecasts are chosen such that the combined forecast is for twelve months ahead. This ensures cross-sectional comparability across earnings forecast revisions.
$Size$	Natural logarithm of equity market capitalization.
SMB	Monthly return to the size factor, obtained from Ken French's website.

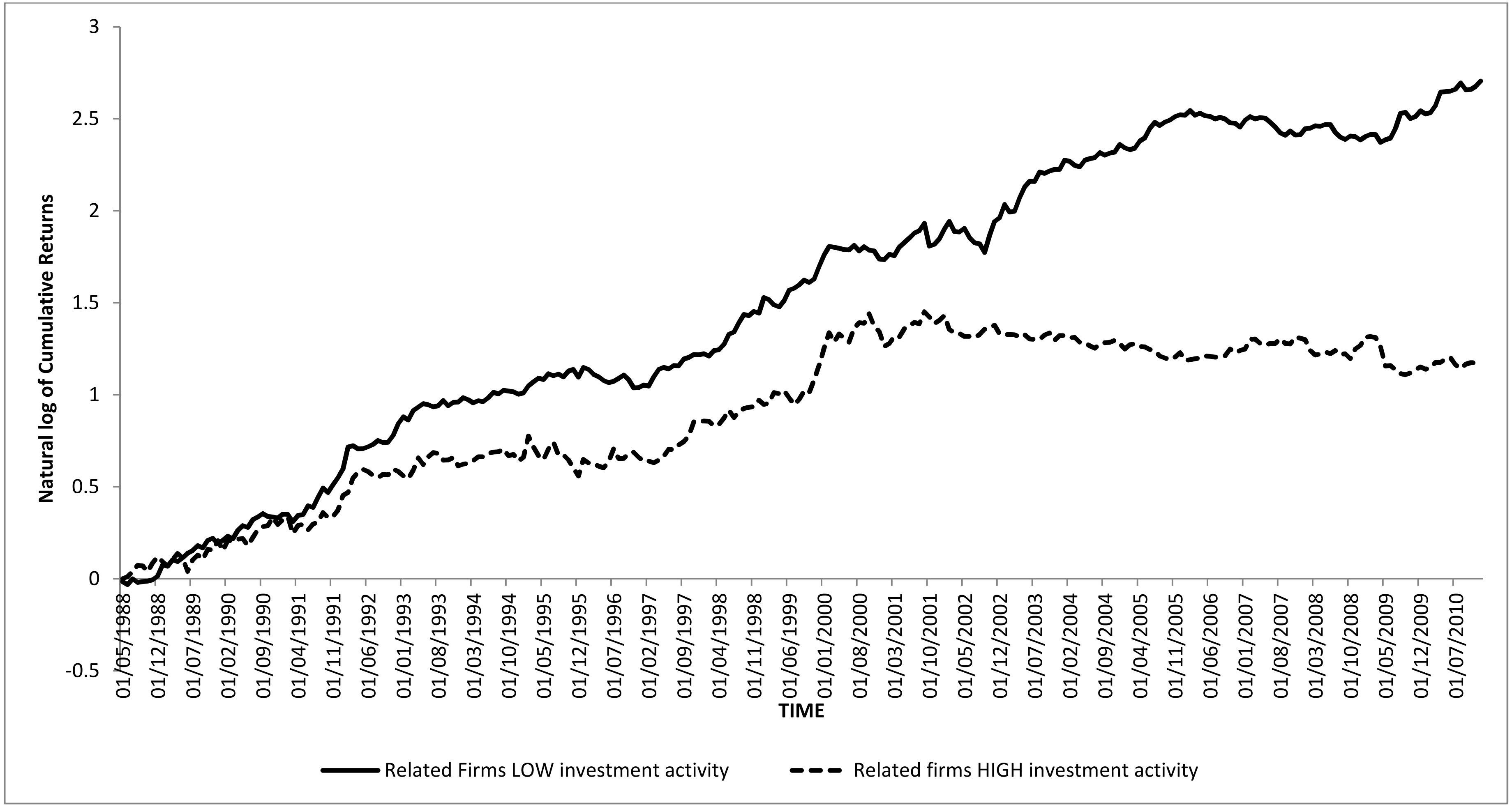

Figure 1: Cumulative Returns associated with inventory growth. Each month firms are sorted into four equal sized portfolios based on the growth in net operating assets (ΔNOA) of related firms. Then, within each group firms are further sorted in four equal sized groups based on their own inventory growth (ΔINV). The bold line plots the returns to a portfolio that takes long (short) positions in firms in the bottom (top) quartile of ΔINV within the <u>top</u> quartile of ΔNOA based on related firms. The dashed line plots the returns to a portfolio that takes long (short) positions in firms in the bottom (top) quartile of ΔINV within the <u>bottom</u> quartile of ΔNOA based on related firms.

Table 1
Sample Details

Panel A: Distribution of real investment activity of the related firms across industry groupings (%)

Industry	Firm/month Obs.	$\Delta NOA^{RELATED}$ Mean	Std. Dev.	Q1	Q3
73A Computer and data processing services	48679	7.03	2.51	6.03	8.74
62 Scientific and controlling instruments	39235	7.44	4.33	3.34	11.27
69B Retail trade	36360	8.90	4.12	6.29	11.27
29A Drugs	31310	8.14	5.08	4.30	9.69
3254 Pharmaceutical and medicine manufacturing	30054	3.37	2.39	1.31	5.15
69A Wholesale trade	28037	5.40	2.44	3.12	7.28
4A00 Retail trade	21462	0.71	2.99	-0.78	2.69
51 Computer and office equipment	19863	6.50	3.34	3.71	8.61
73C Other business and professional services, except medical	19455	6.80	2.76	5.22	8.80
56 Audio, video, and communication equipment	18079	7.34	4.96	2.48	11.24
5112 Software publishers	17618	-0.37	4.71	-4.52	2.45
57 Electronic components and accessories	17483	6.68	3.69	2.74	9.14
3344 Semiconductor and electronic component manufacturing	16961	0.76	3.83	-2.33	3.40
3345 Electronic instrument manufacturing	16926	0.95	3.78	-1.36	3.11
08 Crude petroleum and natural gas	13746	4.08	3.22	1.62	5.62
77A Health services	13298	10.77	8.04	4.31	14.22
4200 Wholesale trade	13248	1.40	3.22	-0.50	3.28
66 Communications, except radio and TV	13124	7.12	4.28	3.52	10.13
74 Eating and drinking places	11620	5.92	2.15	4.61	7.34
68A Electric services (utilities)	10893	5.03	2.36	2.78	6.79
5415 Computer systems design and related services	10153	1.74	2.39	0.48	3.39
334AAudio, video, and communications equipment manufacturing	10022	-0.37	4.09	-4.71	2.91
2110 Oil and gas extraction	9734	5.04	3.65	2.72	6.27
3341 Computer and peripheral equipment manufacturing	9235	0.03	3.51	-3.33	2.81
3391 Medical equipment and supplies manufacturing	8928	3.98	2.53	2.82	5.74
32 Rubber and miscellaneous plastics products	7934	5.91	2.96	3.23	8.02
11+12 Construction	7570	5.33	2.41	3.47	7.05
2211 Power generation and supply	6880	1.78	3.28	0.09	4.51
68B Gas production and distribution (utilities)	6595	4.70	2.45	2.55	6.43
7220 Food services and drinking places	6540	2.17	2.44	0.42	3.96

Panel B: Firm characteristics (N=555,696 firm-months)

Variable	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
RET	0.013	0.208	-0.927	-0.082	0.000	0.082	24.00
NI/P	-0.051	0.300	-7.460	-0.054	0.030	0.063	0.276
ΔINV	0.014	0.051	-0.220	-0.006	0.005	0.031	0.290
BTM	0.620	0.494	0.029	0.288	0.496	0.796	6.570
ROA	0.018	0.180	-1.175	-0.021	0.064	0.118	0.346
$SIZE$	11.918	2.147	4.831	10.36	11.80	13.37	20.21
$Momentum$	0.013	0.090	-0.497	-0.030	0.009	0.048	4.800
$Revision$	0.013	0.074	-1.621	0.002	0.014	0.031	0.908
$BETA$	1.137	0.731	-1.190	0.618	1.054	1.552	4.191
D_Loss	0.361	0.480	0	0	0	1	1
D_Yield	0.006	0.013	0	0	0	0.002	0.182

This table reports summary statistics for the sample. The sample period is 1988-2010. The sample includes 187,397 firm-quarters and 555,696 firm-months. All variables are defined in Appendix II.

Panel A reports the distribution of the real investment activity of the related firms ($\Delta NOA^{RELATED}$) across the 30 most populated industries of our sample. The industry classification follows the Benchmark Input-Output Surveys of the Bureau of Economic Analysis.

Panel B reports firm characteristics. The distributions of the market variables (i.e., Ret, Size, Momentum, Revision, and Beta) are from data pooled over firms and months while the distributions of the accounting based variables are from data pooled over firms and quarters.

To minimize the influence of outliers, the top and bottom 2 percent of observations of the variables each month (quarter) are eliminated except for the stock returns and size.

Table 2
Inventory Growth and Future Firm Fundamentals

ROA (Net Income before extraordinary items /Average Total Assets)

$$ROA_{t+1} = \alpha + \beta_1 ROA_t + \beta_2 \Delta INV_t + \beta_3 BTM_t + \beta_4 Size_t + \beta_5 D\_Loss_t + \beta_6 D\_Yield_t + \beta_7 RET^{RELATED} + e_{t+1} \quad (1)$$

Relation between inventory growth and future firm profitability sorting by $\Delta NOA^{RELATED}$[N=187,397 firm-quarters]

	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	Adj. R^2
Full Sample									
Coefficient	-0.076	0.669	-0.136	-0.003	0.006	-0.015	0.275	0.319	0.461
(t-statistic)	*(-12.24)*	*(41.23)*	*(-9.66)*	*(-1.18)*	*(11.82)*	*(-6.76)*	*(6.85)*	*(3.93)*	
Low $\Delta NOA^{RELATED}$ (N=66,006 firm-quarters)									
Coefficient	-0.075	0.588	-0.153	-0.004	0.007	-0.016	0.064	0.276	0.445
(t-statistic)	*(-10.06)*	*(20.28)*	*(-7.01)*	*(-1.97)*	*(11.64)*	*(-5.03)*	*(1.35)*	*(4.22)*	
Medium $\Delta NOA^{RELATED}$ (N=61,294 firm-quarters)									
Coefficient	-0.056	0.714	-0.113	-0.011	0.004	-0.011	0.351	0.278	0.488
(t-statistic)	*(-7.33)*	*(46.46)*	*(-6.54)*	*(-3.32)*	*(6.83)*	*(-3.81)*	*(6.65)*	*(2.68)*	
High $\Delta NOA^{RELATED}$ (N=60,097 firm-quarters)									
Coefficient	-0.073	0.704	-0.099	-0.002	0.005	-0.021	0.582	0.338	0.462
(t-statistic)	*(-8.16)*	*(39.61)*	*(-5.35)*	*(-0.47)*	*(6.94)*	*(-5.75)*	*(8.43)*	*(2.22)*	
T-statistic on $\beta_2^H - \beta_2^L$			***3.25***						

The reported regression coefficients are from a pooled regression with t-statistics based on standard errors clustered for both time and firm dependencies. To minimize the influence of outliers, the top and bottom two percent of the explanatory variables, except size and returns, were deleted each quarter.

The t-statistic on the difference in the β_2 coefficients between the high and low groups is the t-statistic on the coefficient of the interaction term 'DummyH * ΔInv' in a regression that pools together the high and low groups. All test statistics are based on standard errors clustered for both time and firm dependencies.

All variables are defined in Appendix II.

Table 3 Inventory Growth and Future Stock Returns

$$RET_{t+k} = \alpha + \beta_1 RET_t + \beta_2 \Delta INV_t + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Beta_t + \beta_6 Size_t + \beta_7 Momentum_t + \beta_8 D\_Loss_t + \beta_9 RET^{RELATED} + e_{t+k} \quad (2)$$

Panel A : Relation between inventory growth and future stock returns sorting by $\Delta NOA^{RELATED}$[N=555,696 firm-months]

	k	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	Adj. R^2
Full Sample												
Coefficient	1	0.018	-0.046	-0.052	0.002	0.036	0.004	-0.001	0.011	-0.002	0.306	0.076
(t-statistic)		*(2.74)*	*(-9.11)*	*(-8.05)*	*(1.80)*	*(3.18)*	*(1.16)*	*(-2.83)*	*(1.00)*	*(-1.48)*	*(6.13)*	
Coefficient	2	0.019	-0.004	-0.059	0.002	0.017	0.002	-0.001	0.012	-0.001	0.217	0.048
(t-statistic)		*(2.68)*	*(-0.96)*	*(-8.31)*	*(1.70)*	*(1.35)*	*(1.17)*	*(-2.38)*	*(1.03)*	*(-0.49)*	*(4.06)*	
Coefficient	3	0.020	0.003	-0.054	0.002	0.011	0.002	-0.001	0.006	-0.001	0.166	0.046
(t-statistic)		*(2.85)*	*(0.99)*	*(-7.33)*	*(1.49)*	*(0.93)*	*(1.29)*	*(-2.45)*	*(0.54)*	*(-0.39)*	*(3.29)*	
Low $\Delta NOA^{RELATED}$ (N=196,112 firm-months)												
Coefficient	1	0.023	-0.049	-0.069	0.001	0.016	0.004	-0.002	0.000	-0.002	0.232	0.082
(t-statistic)		*(3.11)*	*(-8.38)*	*(-7.15)*	*(0.73)*	*(1.09)*	*(1.17)*	*(-2.93)*	*(0.01)*	*(-1.37)*	*(3.48)*	
Coefficient	2	0.023	-0.004	-0.071	0.002	0.004	0.002	-0.001	0.009	0.000	0.050	0.052
(t-statistic)		*(2.77)*	*(-0.75)*	*(-7.10)*	*(1.17)*	*(0.23)*	*(1.01)*	*(-2.46)*	*(0.62)*	*(-0.23)*	*(0.74)*	
Coefficient	3	0.024	0.008	-0.066	0.001	0.000	0.002	-0.001	-0.002	-0.001	0.038	0.051
(t-statistic)		*(2.99)*	*(1.60)*	*(-6.36)*	*(0.40)*	*(0.02)*	*(1.10)*	*(-2.54)*	*(-0.12)*	*(-0.72)*	*(0.56)*	
Medium$\Delta NOA^{RELATED}$ (N=182,784 firm-months)												
Coefficient	1	0.008	-0.045	-0.052	0.005	0.039	0.005	-0.001	0.017	-0.002	0.381	0.079
(t-statistic)		*(1.18)*	*(-7.67)*	*(-5.38)*	*(3.38)*	*(2.52)*	*(1.44)*	*(-1.48)*	*(1.38)*	*(-1.04)*	*(3.94)*	
Coefficient	2	0.010	-0.003	-0.056	0.004	0.022	0.004	0.000	0.008	-0.002	0.223	0.052
(t-statistic)		*(1.43)*	*(-0.68)*	*(-5.40)*	*(2.45)*	*(1.47)*	*(2.06)*	*(-1.00)*	*(0.57)*	*(-0.93)*	*(2.03)*	
Coefficient	3	0.014	0.004	-0.053	0.003	0.008	0.003	-0.001	0.007	-0.001	0.122	0.052
(t-statistic)		*(1.96)*	*(0.86)*	*(-4.48)*	*(1.76)*	*(0.54)*	*(1.68)*	*(-1.62)*	*(0.53)*	*(-0.33)*	*(1.14)*	

High$\Delta NOA^{RELATED}$ (N=176,800 firm-months)												
Coefficient	1	0.019	-0.049	-0.032	0.001	0.063	0.004	-0.001	0.016	-0.002	0.354	0.076
(t-statistic)		*(2.58)*	*(-8.47)*	*(-3.16)*	*(0.90)*	*(3.91)*	*(1.07)*	*(-2.94)*	*(1.27)*	*(-1.25)*	*(4.85)*	
Coefficient	2	0.023	-0.008	-0.044	0.002	0.029	0.001	-0.001	0.017	-0.001	0.269	0.051
(t-statistic)		*(2.86)*	*(-1.64)*	*(-3.69)*	*(1.02)*	*(1.76)*	*(0.66)*	*(-2.58)*	*(1.27)*	*(-0.40)*	*(3.38)*	
Coefficient	3	0.021	-0.002	-0.036	0.002	0.029	0.003	-0.001	0.012	-0.001	0.273	0.049
(t-statistic)		*(2.74)*	*(-0.39)*	*(-2.96)*	*(1.42)*	*(1.66)*	*(1.33)*	*(-2.33)*	*(0.90)*	*(-0.39)*	*(3.26)*	
T-statistics on $\beta_2^H - \beta_2^L$												
k=1				***2.65***								
k=2				***1.84***								
k=3				***1.97***								

The reported regression coefficients are mean coefficients from monthly cross sectional regressions.
Within each cross section, stock returns are size weighted (where the weights are the natural log of the securities market capitalization).The *t*-statistics reported in parentheses below coefficient estimates are based on the standard errors of the coefficient estimates across the monthly regressions.The t-statistics reported at the bottom of the panel are the mean difference in the β_2 coefficients between the high and low groups relative to the standard error of that mean difference across the monthly regressions.
To minimize the influence of outliers, the top and bottom two percent of the explanatory variables with the exception of *Size* and *RET*, were deleted each month.
All variables are defined in Appendix II.

Table 4

Portfolio Analyses of the subsample of manufacturing firms
(First sorting on $\Delta NOA^{RELATED}$ then sorting on ΔINV)

Panel A: ΔINV

		$\Delta NOA^{RELATED}$				
		LO	**2**	**3**	**HI**	**HI-LO**
ΔINV	**LO**	-4.72%	-4.14%	-4.02%	-3.61%	1.11%
	2	-0.43%	-0.09%	0.07%	0.35%	0.77%
	3	1.65%	1.88%	2.12%	2.34%	0.69%
	HI	6.94%	7.27%	7.39%	7.88%	0.94%
	HI-LO	11.66%	11.41%	11.41%	11.49%	

Panel B: $\Delta NOA^{RELATED}$

		$\Delta NOA^{RELATED}$				
		LO	**2**	**3**	**HI**	**HI-LO**
ΔINV	**LO**	1.15%	3.13%	4.81%	7.83%	6.69%
	2	1.05%	3.14%	4.75%	7.80%	6.74%
	3	1.12%	3.14%	4.80%	7.89%	6.77%
	HI	1.22%	3.13%	4.81%	8.02%	6.80%
	HI-LO	0.08%	0.01%	0.01%	0.19%	

Panel C: Total Returns

		$\Delta NOA^{RELATED}$					
		LO	**2**	**3**	**HI**	**HI-LO**	**T-stat**
ΔINV	**LO**	2.10%	1.70%	1.80%	1.41%	-0.68%	-2.27
	2	1.41%	1.24%	1.40%	0.85%	-0.56%	-1.55
	3	1.25%	1.09%	1.17%	0.60%	-0.65%	-1.72
	HI	0.87%	0.90%	0.99%	0.70%	-0.17%	-0.39
	HI-LO	-1.23%	-0.80%	-0.81%	-0.71%	**0.52%**	**2.08**
	T-stat	-6.13	-4.17	-4.48	-2.99		

Panel D: DGTW characteristic adjusted returns

		$\Delta NOA^{RELATED}$					
		LO	**2**	**3**	**HI**	**HI-LO**	**T-stat**
ΔINV	**LO**	0.91%	0.50%	0.51%	0.43%	-0.48%	-2.10
	2	0.31%	0.15%	0.24%	0.06%	-0.25%	-0.97
	3	0.22%	0.03%	0.02%	-0.13%	-0.35%	-1.21
	HI	-0.16%	-0.19%	-0.15%	-0.11%	0.05%	0.04
	HI-LO	-1.07%	-0.69%	-0.67%	-0.54%	**0.53%**	**2.14**
	T-stat	-5.88	-3.77	-4.12	-2.43		

Panel E: 4-factor 'alpha'

		$\Delta NOA^{RELATED}$					
		LO	**2**	**3**	**HI**	**HI - LO**	**T-stat**
ΔINV	**LO**	1.09%	0.75%	0.78%	0.68%	-0.41%	-1.46
		(4.73)	*(3.44)*	*(4.13)*	*(2.92)*		
	2	0.39%	0.29%	0.39%	0.27%	-0.11%	-0.38
		(2.20)	*(1.88)*	*(2.85)*	*(1.40)*		
	3	0.34%	0.15%	0.18%	0.04%	-0.29%	-1.00
		(2.15)	*(1.02)*	*(1.10)*	*(0.20)*		
	HI	0.04%	-0.04%	0.00%	0.07%	0.03%	0.17
		(0.23)	*(-0.25)*	*(0.01)*	*(0.34)*		
	HI - LO	-1.06%	-0.79%	-0.78%	-0.62%	**0.44%**	**1.62**
	T-stat	-5.34	-3.99	-4.55	-2.79		

For each month stocks are first sorted into four equal groups based on the level of the real investment activity of the related firms ($\Delta NOA^{RELATED}$). Then, within each group, stocks are further sorted into four groups based on the change in firm's level inventories (ΔINV).

Panels A and B report arithmetic means of portfolio characteristics.

Panel C reports average size weighted monthly total returns from forming portfolios each month. The reported t-statistics are the mean return differences between returns for the high and low portfolios indicated relative to the standard error of that mean estimated from the time series of return differences.

Panel D is the same as Panel C except returns are characteristic adjusted following Daniel, Grinblatt, Titman and Wermers (1997).

Panel E reports intercepts (with t-statistics in parenthesis) from regressing portfolio monthly excess returns (over the return on the U.S. one-month Treasury bill) in the time-series regressions on excess returns associated with market (MKT), size (SMB), book-to-price (HML) and momentum (UMD) factors. The factor returns for MKT, SMB, HML and UMD factors and the one-month Treasury return were obtained from Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html.

Table 5 Inventory Growth and Future Analyst Forecast Revisions

$$Revision_{t+k} = \alpha + \beta_1 Revision_t + \beta_2 \Delta INV_t + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Momentum_t + \beta_6 D\_Loss_t + \beta_7 RET^{RELATED} + e_{t+k} \quad (4)$$

Panel A : Relation between inventory growth and future analyst revisions sorting by $\Delta NOA^{RELATED}$[N=268,736 firm-months]

	k	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	Adj. R^2
Full Sample										
Coefficient	1	0.010	0.218	-0.020	-0.002	-0.127	0.165	0.008	0.165	0.120
(t-statistic)		*(9.50)*	*(27.73)*	*(-3.14)*	*(-2.16)*	*(-17.16)*	*(23.77)*	*(7.81)*	*(6.89)*	
Coefficient	2	0.010	0.162	-0.022	0.000	-0.139	0.139	0.008	0.145	0.091
(t-statistic)		*(9.09)*	*(26.42)*	*(-3.26)*	*(-0.14)*	*(-18.77)*	*(18.34)*	*(7.49)*	*(6.04)*	
Coefficient	3	0.009	0.196	-0.020	0.001	-0.129	0.081	0.005	0.137	0.091
(t-statistic)		*(8.24)*	*(31.63)*	*(-3.25)*	*(1.27)*	*(-17.10)*	*(13.89)*	*(6.00)*	*(5.43)*	
Low $\Delta NOA^{RELATED}$ (N=94,928 firm-months)										
Coefficient	1	0.010	0.220	-0.029	-0.001	-0.135	0.162	0.009	0.152	0.130
(t-statistic)		*(7.42)*	*(25.51)*	*(-3.15)*	*(-0.98)*	*(-11.76)*	*(20.00)*	*(6.38)*	*(3.69)*	
Coefficient	2	0.010	0.161	-0.026	0.001	-0.148	0.133	0.009	0.092	0.103
(t-statistic)		*(6.52)*	*(18.06)*	*(-2.70)*	*(0.79)*	*(-11.51)*	*(15.12)*	*(6.76)*	*(2.18)*	
Coefficient	3	0.008	0.190	-0.021	0.002	-0.137	0.077	0.005	0.064	0.102
(t-statistic)		*(4.60)*	*(23.18)*	*(-1.98)*	*(1.53)*	*(-10.17)*	*(10.37)*	*(4.38)*	*(1.45)*	
Medium $\Delta NOA^{RELATED}$ (N=90,848 firm-months)										
Coefficient	1	0.009	0.206	-0.019	-0.001	-0.120	0.162	0.007	0.264	0.124
(t-statistic)		*(5.28)*	*(20.44)*	*(-2.08)*	*(-1.20)*	*(-11.84)*	*(19.26)*	*(4.59)*	*(4.47)*	
Coefficient	2	0.012	0.162	-0.023	-0.001	-0.121	0.137	0.007	0.243	0.102
(t-statistic)		*(5.44)*	*(19.23)*	*(-2.97)*	*(-0.97)*	*(-11.19)*	*(15.88)*	*(3.75)*	*(3.89)*	
Coefficient	3	0.011	0.198	-0.016	0.000	-0.108	0.089	0.004	0.246	0.107
(t-statistic)		*(5.16)*	*(24.67)*	*(-2.04)*	*(-0.05)*	*(-8.26)*	*(11.25)*	*(2.54)*	*(4.10)*	

High $\Delta NOA^{RELATED}$ (N=82,960 firm-months)

Coefficient	1	0.010	0.218	-0.004	-0.003	-0.118	0.171	0.008	0.113	0.130
(t-statistic)		*(7.72)*	*(20.15)*	*(-0.37)*	*(-2.15)*	*(-10.19)*	*(17.07)*	*(5.15)*	*(3.28)*	
Coefficient	2	0.010	0.159	-0.003	0.000	-0.145	0.149	0.008	0.167	0.102
(t-statistic)		*(6.72)*	*(17.86)*	*(-0.28)*	*(-0.10)*	*(-10.54)*	*(13.77)*	*(4.57)*	*(3.88)*	
Coefficient	3	0.009	0.194	-0.012	0.001	-0.128	0.090	0.007	0.160	0.101
(t-statistic)		*(6.25)*	*(22.67)*	*(-1.21)*	*(0.97)*	*(-8.95)*	*(9.91)*	*(4.88)*	*(3.91)*	
T-statistics on $\beta_2^H - \beta_2^L$										
k=1				***2.21***						
k=2				***2.16***						
k=3				***0.69***						

The reported regression coefficients are mean coefficients from monthly cross sectional regressions.
Within each cross section, consensus EPS revisions are size weighted (where the weights are the natural log of the securities market capitalization).The *t*-statistics reported in parentheses below coefficient estimates are based on the standard errors of the coefficient estimates across the monthly regressions.The t-statistics reported at the bottom of the panel are the mean difference in the β_2 coefficients between the high and low groups relative to the standard error of that mean difference across the monthly regressions.
To minimize the influence of outliers, the top and bottom two percent of the explanatory variables, except size and return, were deleted each month.
All variables are defined in Appendix II.

Table 6: Robustness test: Manufacturing firms

Panel A: Relation between inventory growth and future firm profitability sorting by $\Delta NOA^{RELATED}$ [N=109,301 firm-quarters]

$$ROA_{t+1} = \alpha + \beta_1 ROA_t + \beta_2 \Delta INV_t + \beta_3 BTM_t + \beta_4 Size_t + \beta_5 D\_Loss_t + \beta_6 D\_Yield_t + \beta_7 RET^{RELATED} + e_{t+1} \quad (1)$$

	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	Adj. R^2
Full Sample									
Coefficient	-0.074	0.684	-0.192	-0.003	0.006	-0.016	0.283	0.367	0.485
(t-statistic)	*(-8.91)*	*(40.07)*	*(-9.92)*	*(-0.96)*	*(8.92)*	*(-5.25)*	*(4.65)*	*(4.03)*	
Low $\Delta NOA^{RELATED}$ (N=38,323 firm-quarters)									
Coefficient	-0.080	0.599	-0.188	-0.002	0.007	-0.019	0.046	0.326	0.455
(t-statistic)	*(-7.65)*	*(19.05)*	*(-7.04)*	*(-0.78)*	*(8.93)*	*(-4.26)*	*(0.64)*	*(4.65)*	
Medium $\Delta NOA^{RELATED}$ (N=36,179 firm-quarters)									
Coefficient	-0.049	0.724	-0.171	-0.012	0.004	-0.013	0.311	0.323	0.514
(t-statistic)	*(-4.86)*	*(39.17)*	*(-7.22)*	*(-2.63)*	*(4.80)*	*(-3.15)*	*(4.34)*	*(2.57)*	
High$\Delta NOA^{RELATED}$ (N=34,799 firm-quarters)									
Coefficient	-0.061	0.726	-0.155	-0.007	0.004	-0.020	0.662	0.378	0.494
(t-statistic)	*(-4.89)*	*(39.86)*	*(-6.22)*	*(-1.67)*	*(4.25)*	*(-4.08)*	*(5.93)*	*(2.38)*	
T-statistic on $\beta_2^H - \beta_2^L$			***2.03***						

Panel B. Relation between inventory growth and future stock returns sorting by $\Delta NOA^{RELATED}$[N=324,768 firm-months]

$$RET_{t+1} = \alpha + \beta_1 RET_t + \beta_2 \Delta INV_t + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Beta_t + \beta_6 Size_t + \beta_7 Momentum_t + \beta_8 D\_Loss_t + \beta_9 RET^{RELATED} + e_{t+k} \quad (2)$$

	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	Adj. R^2
Full Sample											
Coefficient	0.021	-0.048	-0.053	0.002	0.018	0.004	-0.002	0.004	-0.003	0.313	0.078
(t-statistic)	*(2.86)*	*(-9.33)*	*(-6.91)*	*(1.36)*	*(1.39)*	*(1.15)*	*(-3.05)*	*(0.34)*	*(-1.86)*	*(6.14)*	
Low $\Delta NOA^{RELATED}$ (N=109,888 firm-months)											
Coefficient	0.024	-0.051	-0.070	0.001	0.006	0.006	-0.002	0.001	-0.002	0.337	0.083
(t-statistic)	*(2.81)*	*(-7.60)*	*(-5.36)*	*(0.30)*	*(0.35)*	*(1.48)*	*(-2.76)*	*(0.05)*	*(-1.22)*	*(3.98)*	
Medium $\Delta NOA^{RELATED}$ (N=111,520 firm-months)											
Coefficient	0.008	-0.049	-0.058	0.005	0.019	0.004	-0.001	0.015	-0.003	0.249	0.083
(t-statistic)	*(1.03)*	*(-7.40)*	*(-4.76)*	*(3.14)*	*(1.05)*	*(0.96)*	*(-1.77)*	*(0.99)*	*(-1.61)*	*(2.51)*	
High $\Delta NOA^{RELATED}$ (N=103,360 firm-months)											
Coefficient	0.017	-0.051	-0.034	0.000	0.056	0.005	-0.002	-0.006	-0.003	0.527	0.079
(t-statistic)	*(1.94)*	*(-8.19)*	*(-2.90)*	*(0.24)*	*(2.79)*	*(1.40)*	*(-2.83)*	*(-0.40)*	*(-1.40)*	*(3.76)*	
T-statistics on $\beta_2^H - \beta_2^L$			***2.17***								

Panel C : Relation between inventory growth and future analyst revisions sorting by $\Delta NOA^{RELATED}$[N=150,144 firm-months]

$$Revision_{t+1} = \alpha + \beta_1 Revision_t + \beta_2 \Delta INV_t + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Momentum_t + \beta_6 D\_Loss_t + \beta_7 RET^{RELATED} + e_{t+k} \quad (4)$$

	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	Adj. R^2
Full Sample									
Coefficient	0.010	0.214	-0.018	-0.001	-0.150	0.168	0.009	0.166	0.126
(t-statistic)	*(8.12)*	*(25.35)*	*(-2.31)*	*(-1.12)*	*(-15.27)*	*(20.40)*	*(7.21)*	*(5.63)*	
Low $\Delta NOA^{RELATED}$ (N=50,864 firm-months)									
Coefficient	0.013	0.223	-0.023	-0.002	-0.170	0.153	0.007	0.217	0.140
(t-statistic)	*(7.49)*	*(19.62)*	*(-2.21)*	*(-1.44)*	*(-10.12)*	*(14.68)*	*(4.02)*	*(3.69)*	
Medium $\Delta NOA^{RELATED}$ (N=51,952 firm-months)									
Coefficient	0.008	0.189	-0.012	0.000	-0.161	0.169	0.011	0.252	0.137
(t-statistic)	*(3.87)*	*(16.04)*	*(-1.05)*	*(-0.26)*	*(-11.30)*	*(16.18)*	*(5.10)*	*(3.95)*	
High $\Delta NOA^{RELATED}$ (N=47,328 firm-months)									
Coefficient	0.008	0.222	-0.004	-0.002	-0.110	0.181	0.010	0.207	0.143
(t-statistic)	*(4.26)*	*(19.01)*	*(-0.37)*	*(-1.07)*	*(-7.09)*	*(16.53)*	*(4.90)*	*(3.45)*	
T-statistics on $\beta_2^H - \beta_2^L$			***1.41***						