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Inventories and the Credit Crisis:

A Chicken and Egg Situation.

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Abstract

Inventories are known to play a large role in business cycles, but the causal relationship is not entirely understood—do inventory cycles generate business cycles, or vice versa? In operations management theory, modeling choice pre-determines the role of inventories. Production smoothing models dictate that inventories follow production decisions; Order-Up-To models dictate that inventories drive production decisions. Empirical observations, however, show that inventories are both a cause and an effect of production decisions. We hypothesize that –in real life– target inventory levels are dynamic and are adjusted in response to not only changes in demand forecast but also fluctuating cost considerations. We develop a two-echelon structural model of inventory decisions using financial data for 6040 unique supplier-customer dyads for the years 1984–2013 to investigate downstream inventory adjustments and their influence on upstream firms. The model shows that suppliers react to arbitrary downstream inventory adjustments over and above the demand changes, revealing a new explanation for transient shocks getting amplified upstream. Our results show that inventory cost ratios are dynamic, and support the hypothesis that they follow economic and financial sentiment such as liquidity considerations and GDP growth rates.

1 Introduction

The importance of inventories in the economy has long been understood. Economists agree that fluctuations in inventory investment account for more than a third of the quarterly change in U.S. GDP (Fitzgerald, 1997)[1]. Blinder (1990) famously remarked: “Business cycles are, to a surprisingly large degree, inventory cycles”. Yet, the precise role of inventories in these cycles is still an open question. Do inventory cycles cause business cycles or is it the other way around?

At a smaller scale, the role of inventories in the day-to-day operations of a firm is, to a large extent, determined by its production strategy[2]. When convex production costs dominate, firms benefit from maintaining production as constant as possible. As a result, such firms use inventories as a buffer to absorb demand uncertainty. This is the intuition behind production smoothing.

When inventory-related costs dominate, on the other hand, firms benefit from maintaining a stable inventory level. In these firms, inventories drive production decisions with the objective of minimizing inventory variability around a pre-defined target level. This is the intuition behind Order-Up-To policies.

In this view, inventories can be classified as either an adjustment variable (i.e. the consequence of production decisions) or as a decision variable (i.e. the driver of production decisions). Reality, however, is more subtle. Neither pure production smoothing nor Order-Up-To models fully explain empirical observations. As a consequence, hybrid models have been developed: Smoothing models that incorporate inventory-driven adjustments (Blinder, 1990; Ramey and West, 1999) as well as generalized Order-Up-To models that incorporate a smoothing component (Dejonckheere et al., 2003; Chen and Lee, 2009). These models, however, assume that relative costs are constant in time; modeled firms do not change their smoothing strategy nor their inventory targets[3].

In this paper, we argue that target inventory levels, in practice, are dynamic. Firms systematically adjust their targets responding (among other causes) to fluctuating cost considerations. As a consequence, the customer demand faced by upstream firms depends directly on downstream inventory decisions.

This view is motivated by a series of recent developments. Udenio et al. (2012) conducted a firm-level study using the 2008 financial crisis as a natural experiment. Their observations

[1]Depending on time period analyzed, estimations of how much inventory fluctuations account for post-war GDP fluctuations go from 44% to 87%, (Blinder and Maccini, 1991; Wang and Wen, 2009).

[2]Even though we use the term “production”, the discussion also applies to non-manufacturing firms where “production” is replaced by “orders”.

[3]Several models do however, compute target inventory levels as a function of a demand forecast that is updated with each subsequent demand observation. In these models, changes in the demand forecast result in changes in the target inventory level. However, it is not a systematic one; the underlying target inventory, expressed as a function of the demand forecast, remains constant.

are consistent with the hypothesis that inventories are used as an instrument of liquidity in times of need. Drastic reductions in inventory investment free up much needed cash. Similarly, Pesch and Hoberg (2013) used secondary data to show that inventories are used as a significant source of liquidity by firms in financial distress, independent of global crises.

Burns and Sivazlian (1978) analyzed inventory adjustments from a different perspective, using numerical experimentation in a serial supply chain. Without assumptions regarding the underlying motives, they find that inventory adjustments executed by downstream echelons trigger transient changes in their orders that cause an overreaction in upstream echelons because suppliers cannot distinguish transient from permanent changes in demand. They identify this "false ordering" phenomenon as a purely structural issue, product of the delays inherent to the transmission of information, and propose a modified ordering rule that takes this into account as a way of solving it. Intuitively, their solution implies separating the component of incoming orders that corresponds to downstream inventory fluctuations from the component that corresponds to "actual" demand, and reacting only to the latter.

More recently, the interaction between different echelons in a supply chain has been the focus of the information-sharing literature. The objective of this stream of the literature is, as Cachon and Fisher (2000) put it, to test "the general belief within industry that capturing and sharing real-time demand information is the key to improved supply chain performance". Insights from the analytical information-sharing literature indicate that, in general, upstream firms benefit the most from the sharing of information among supply chain players, and that the benefits depend on the type of demand observed downstream (and thus, the amount of non-inferable information that can be obtained through sharing). Most studies in this stream, however, assume rational firms with actions modeled through Order-Up-To policies, the knowledge of which is also shared among a supply chain. Chen and Lee (2009) drop the latter assumption, noting that in practice, it is rather rather bold to assume that firms share details about their ordering policies. They advocate for the sharing of order projections as it eliminates guesswork from the part of the suppliers. In fact, they note that this allows suppliers to separate order uncertainty from order variability.

Separating order uncertainty from order variability, according to Bray and Mendelson (2013), is the key to disentangle the effects of production smoothing and the bullwhip effect. They argue that the goal of production smoothing is to protect against order uncertainty, not against order variability—and thus, that empirical measures of production smoothing should not benchmark order variability against demand variability but against what the theoretical order variability would be in the absence of production adjustment costs.

In this paper, we use secondary data at two levels of a supply chain (supplier/customer pairs) to investigate the causes of downstream inventory decisions, and their influence on upstream orders. Using firm level data, we find evidence of an overreaction of upstream firms to downstream inventory adjustments, and track down systematic factors that drive fluctuations of safety inventories. Methodologically, we use an econometric model specification to estimate the influence of inventory changes in orders, and structural modeling of the cost factors to estimate the systematic adjustment of inventory buffers.

The contribution of this paper to the literature is threefold: First, we identify the portion of order uncertainty that corresponds to downstream safety stock changes and analyze its influence on upstream order generation. Second, we extend the structural modeling methodology of Olivares et al. (2008) to estimate the cost ratios used by firms in a multi-period setting. Finally, we show evidence of a systematic adjustment of target inventories that follows economic and financial conditions.

The remainder of this paper is organized as follows. In Section 2, we introduce the data used and detail the construction of supplier/customer firm pairs. We present the econometric inventory model and related hypothesis in Section 3, the structural cost model and related hypothesis in Section 4. We follow in Section 5 with the results of our analysis, and conclude in Section 6.

2 Data

To quantify the effect of downstream inventory decisions on upstream firms, the first step we take is to collect firm-level data and define explicit relationships between upstream and downstream firms. To do so, we adopt an approach pioneered by the financial community. In this approach we use the disclosure of major customers, contained in the annual financial statements of public firms, to identify explicit relationships between firms. Recent examples of such an approach include Fee and Thomas (2004), who use customer-supplier relationship data to quantify the effect of horizontal mergers in post-merger operating performance; Fee et al. (2006), who investigate the customer-supplier relationships to determine the conditions under which customers own equity of their suppliers; and Cohen and Frazzini (2008), who study whether stock returns can be predicted through knowledge of economic links between companies. In §2.1 we detail the methodology we use to construct supplier-customer pairs, and in §2.2 we summarize the collection of the remaining financial data.

2.1 Customer-Supplier Firm Pairs

The regulation of the Statement of Financial Accounting Standards (SFAS) No. 131 requires firms to disclose any customer that represents at least 10% of the revenues for a given fiscal year. This information is included in Compustat's *customer segment database*, which we access through Wharton Research Data Services (WRDS) of the University of Pennsylvania. We extract the identity of supplier-customer firm pairs for the $1976-2012$ period.[4] Firms, however, report the identity of their customers as a plain-text string in a non-standardized

[4]Regulation SFAS 131, issued by the Financial Accounting Standards Board in 1997, has been effective for fiscal years beginning after December 15th 1997. The customer disclosure requirements in this regulation carried over from regulation SFAS 14, effective since December 1976.

way. Therefore, spelling mistakes exist in the data, as well as spelling variations and abbreviations that vary across suppliers and periods. We apply a three-step procedure, inspired by the financial research literature (Fee and Thomas, 2004), to map the reported plain-text customer names to Compustat's unique customer identifier keys. In the first step, we perform a 1-1 match between the reported company names and the Compustat company name and assign the corresponding customer identifier key to successful matches.

In the second step, we apply a partial string matching algorithm, based on the normalized Levenshtein distance, to the remaining data[5].

The partial string matching algorithm calculates the normalized Levenshtein distance between all potential combinations of reported and Compustat company names, and flags them as a potential match when $\overline{lev}_{a,b} < 0.25$. Potential matches are then manually checked against (a) possible ambiguities (in cases where any ambiguity exists –such as for example a match for 'continental', a name that appears in numerous companies– the potential matches are dropped), and (b) business segments, by confirming that the business segment reported by the supplier is compatible with the business segment of the matched customer.

Finally, we sort all remaining unmatched observations by the frequency of appearances of the reported customer name and manually match the top 16 firms (these represent $\sim 16\%$ of the data).

Compustat's *customer segment database* contains a discontinuity in the year 2006: No data is available for firms whose fiscal year ends in Q4 2006, causing the number of records for the year to be abnormally low.[6] To overcome this, we assume that companies that are linked both in 2005 and 2007 are also linked in 2006 and update the links accordingly.

As a reference, Figure 1 shows the number of records per quarter and the quarter-on-quarter change in US GDP for the entire period. Because the 1976-1984 period is marked by a large instability in the GDP time series and relatively few data-points, we drop the observations from 1976 until 1983 from the dataset. The final firm pair database includes 24825 unique yearly pairs.

2.2 Customer and Supplier Financial Data

To take advantage of the reporting frequency of the *quarterly fundamentals database*, we assume that each of the firm pairs we have defined are involved in trading during the four quarters of the reported fiscal year, and thus populate the firm pair database with financial information from said database. Following Cachon et al. (2007), we use cost of goods sold (COGS) as a proxy for demand (d), production (q) as a proxy for orders, and calculate production with the balance equation $q_t = d_t + i_t - i_{t-1}$, where i_t is the reported total

[5]The Levenshtein distance between strings a and b ($lev_{a,b}$) is defined as *The smallest number of insertions, deletions, and substitutions required to change string a into string b* (Levenshtein, 1966). The normalized Levenshtein distance ($\overline{lev}_{a,b}$) is defined as $lev_{a,b}/\min(|a|, |b|)$, where $|i|$ is the length of string i.

[6]This is due to significant changes made to Compustat's databases in the year 2006.

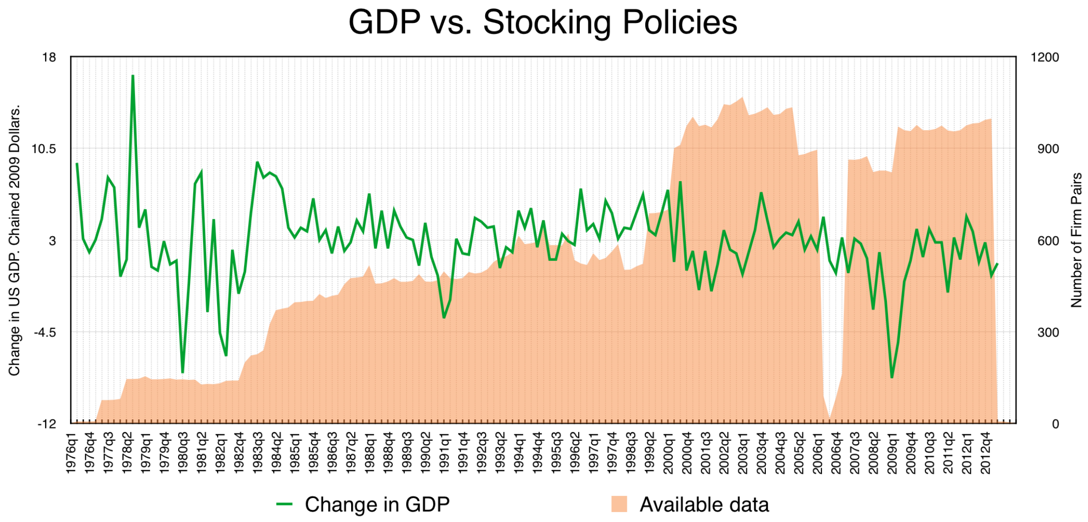

Figure 1 – Available data per quarter and GDP variation

inventory at the end of the period t. We delete observations with negative, or missing, values for inventories and/or sales from the sample.

Since fiscal year endings vary across firms, we pair customers and suppliers independently using calendar dates. The final sample contains 77886 quarterly observations, representing 6040 unique supplier-customer relationships between 1984 and 2013. Table 1 shows summary statistics for our dataset.

The firm size distribution is calculated on the basis of average COGS over the entire sample. We can see that the nature of our supplier-customer pairing strategy, where we can only identify customers that represent more than 10% of a firm's revenues, biases the sample towards large customers with a large number of relatively smaller suppliers. We analyze the influence of this bias on our results in an appendix, presented at the end of this paper.

Table 1 – Summary Statistics

	Min	Max	Mean	SD	1st Quartile	Median	3rd Quartile
Number of suppliers in the sample per quarter	5	711	501	142	391	533	609
Number of customers in the sample per quarter	4	349	220	110	101	277	321
Frequency-Weighed link duration (quarters)	1	140	14	15	4	8	17
Supplier size percentile	0.01	0.99	0.70	0.82	0 .24	0.42	0.62
Customer size percentile	0.01	0.99	0.99	0.99	0 .91	0.98	0.99
Number of customers per supplier	1	27	3.78	3.20	2	3	5
Number of suppliers per customer	1	351	102.1	112.1	11	53	203

Table 2 shows additional sales and inventory statistics of the firms contained in our dataset, grouped according to their 2-digit NAICS code. Note that while we constrain the suppliers to the manufacturing sector, customers belong to a range of industries. Nevertheless, manufacturing, retail, and wholesale customers make up the vast majority of the sample: 58%, 19% and 10% respectively.

Table 2 – Summary statistics by NAICS code for suppliers (top) and customers (bottom)

NAICS Code	Frequency	COGS				Total Inventory			
Supplier		Mean	25th Percentile	Median	75th Percentile	Mean	25th Percentile	Median	75th Percentile
31	8070	294.7	17.8	56.5	217.4	237.1	15.3	53.8	188.6
32	17120	181.4	5.9	20.8	109.6	224.9	1.6	15.1	100.7
33	52696	252.6	7.3	30.7	135.1	156.9	7.3	27.2	98.3
Customer									
11	18	662.0	350.0	555.5	710.0	1387.0	1130.0	1298.5	1387.0
21	323	2740.6	347.3	912.0	2934.0	846.8	109.2	386.3	962.0
22	320	1705.4	682.8	1615.0	2405.0	566.6	182.2	379.0	786.0
23	219	2540.5	1332.6	1901.0	3235.5	1637.2	819.7	1094.1	1519.8
31	1129	1635.0	396.9	1113.0	2034.0	1153.4	361.0	716.6	1204.7
32	6829	3478.5	344.6	976.0	2689.3	2261.6	423.4	1560.5	3021.5
33	34057	10381.5	1318.9	4880.1	19502.0	4716.9	909.0	3150.0	6845.0
42	7191	12705.2	3307.3	12883.5	21303.0	4529.5	1373.3	4822.4	7585.3
44	3717	6381.8	1148.0	5751.2	11049.0	4851.3	1333.2	3250.0	8314.0
45	10105	15245.5	2408.8	6178.0	17684.0	9765.5	2656.0	5200.0	14682.0
48	269	1924.9	1353.0	1897.0	2455.0	312.0	164.0	257.0	458.0
49	17	7214.9	6957.0	7402.0	7937.0	408.6	389.0	413.0	440.0
51	3097	3919.9	1066.1	2378.2	7105.0	1053.5	0.0	381.0	1464.6
53	56	343.6	13.7	122.0	763.5	18.2	2.7	9.0	30.4
54	989	4670.7	1090.5	2103.0	10856.0	2910.2	816.5	2483.6	4858.0
56	43	1636.0	1689.0	1906.0	2044.0	84.0	75.0	80.0	92.0
61	9	358.5	342.4	358.0	366.8	28.3	27.6	29.3	31.5
62	146	488.3	63.9	573.4	785.9	48.2	4.6	54.9	77.9
71	1	14.1	14.1	14.1	14.1	3.3	3.3	3.3	3.3
72	205	1736.8	422.7	1861.0	2801.7	84.9	33.1	85.7	115.1
81	12	401.6	384.8	402.2	421.4	31.6	30.9	31.4	33.7
99	1243	11938.2	8956.0	11880.0	15133.5	8374.2	5026.0	6735.0	11744.0

3 Replenishment Model

In this section, we use a non-stationary-demand inventory model to motivate hypotheses related to the influence of downstream inventory changes on upstream orders. In §3.1 we present the single echelon inventory model. We derive the hypotheses in §3.2, detail the 2-echelon model in §3.3, present a forecasting model in 3.4, and finally, present the econometric specification of the model in §3.5.

3.1 Single Echelon Model

Let q_t be the order placed at time t. We consider a single-item adaptive base-stock control policy of the form:

$$q_t = d_t + L(F_{t+1} - F_t), \tag{3.1}$$

where L is the lead time, and F_{t+1} the forecast of d_t calculated at the end of period t. We assume that we (1) observe demand, (2) calculate the forecast for the next period, (3) place the orders for the period, (4) receive the orders placed L periods ago, and finally (5) fulfill demand from inventory (backlogging any demand that cannot be met). Graves (1999) adopts this policy for a multi-echelon environment with non-stationary demand, arguing that it is a myopic policy that, while not necessarily optimal, is a "reasonable extension of the order-up-to policy". The policy contains two terms; the left term replenishes the period's demand, and the right term modifies the base-stock level in proportion to the change in forecast, to account for changes in the mean lead-time demand.

We propose, for later econometric estimation, a firm-level model based upon this replenishment rule. For the purpose, we assume that a firm controls the entirety of their purchases equally and that lead times are constant. Using this model with firm-level data is in line with Rumyantsev and Netessine's (2007)[7] empirical finding that aggregate inventory changes are positively associated with sales surprise, a term introduced by Gaur et al. (2005). Sales surprise is defined as the ratio of sales to demand forecast, and thus quantifies unexpectedly high (or low) sales. Additionally, suppose that a rational decision maker on behalf of firm i uses a variant of the proposed policy whereupon she can arbitrarily adjust the order quantity by an amount u in every period:

$$q_{i,t} = d_{i,t} + L_i(F_{i,t+1} - F_{i,t}) + u_{i,t}. \tag{3.2}$$

Here, we see that the base-stock level is adjusted proportionally to the change in mean lead-time demand (as in Equation (3.1)), but is also adjusted discretionarily in every period through the adjustment quantity u_t, of which we make no assumptions yet. We call the first kind of adjustment the 'planned change in inventory buffer', and the second the 'unplanned change in inventory buffer'. For notational convenience, we denote the change in the forecast as $\Delta F_{i,t}$,

$$\Delta F_{i,t} = F_{i,t+1} - F_{i,t}, \tag{3.3}$$

then we have:

$$\underbrace{q_{i,t}}_{\text{Orders}} = \underbrace{d_{i,t}}_{\substack{\text{Demand}\\ \text{Replacement}}} + \underbrace{\beta^1 \, \Delta F_{i,t}}_{\substack{\text{Planned change}\\ \text{in inventory buffer}}} + \underbrace{u_{i,t}}_{\substack{\text{Unplanned change}\\ \text{in inventory buffer}}}, \tag{3.4}$$

where β^1 is a coefficient, to be estimated, that contains information on the replenishment lead times. When $u_{i,t} = 0$, this is equivalent to the policy from Equation (3.1) with $\beta^1 = L$.

[7] Rumyantsev and Netessine (2007) tested several hypothesis derived from traditional inventory theory using a multiplicative inventory model with which they quantified the influence of several independent variables. Our specification differs from theirs in that we test a linear inventory model and consider both positive as well as negative deviations from the forecasted values.

3.2 Hypotheses Development

Changes in base-stock levels (inventory buffers), whether "planned" or "unplanned", materialize through changes in order quantities. Burns and Sivazlian (1978) show that the transient nature of such changes in downstream orders contribute to the amplification of order variability in serial supply chains because they are interpreted as persistent demand changes by upstream firms, which triggers an overreaction. Analytical work shows that information sharing can be used to reduce the amplification—with the caveat of specific demand distributions, or assumptions on the knowledge of the underlying replenishment rules (Chen and Lee, 2009).

Experimental work based upon behavioral operations theory, on the other hand, drops such assumptions in favor of human beings making decisions in the context of a supply chain simulation—usually some version of the beer distribution game. This stream of literature suggests that the human biases that are a cause of the bullwhip effect are robust to information sharing. They show that, even when controlling for all operational causes of the bullwhip effect, and under full information sharing, the amplification of orders in a supply chain persists (Croson and Donohue, 2006).

Our first hypothesis comes from the combination of our inventory model with the insights mentioned above. When analysing the customer-supplier data pairs, we expect that when a downstream firm executes a planned change in their inventory buffer, the upstream firm will overreact to this change and will adapt his inventory buffer proportionally to the downstream change.

H 1 *Changes in upstream inventories are positively associated with planned changes in downstream inventory buffers.*

Similarly, we expect that unplanned changes in downstream inventory buffers will have a similar effect on upstream inventories.

H 2 *Changes in upstream inventories are positively associated with unplanned changes in downstream inventory buffers.*

3.3 Two-Echelon Model

To test Hypotheses 1 and 2, we develop a two-echelon model. We identify customers with the subscript c, and suppliers with the subscript s so that we can express the orders of customer c at time t as:

$$q_{c,t} = d_{c,t} + \beta^1 \Delta F_{c,t} + u_{c,t}. \tag{3.5}$$

Furthermore, we propose the following model of supplier s's orders to test hypotheses 1 and 2:

$$q_{s,t} = d_{s,t} + \beta^2\, \Delta F_{s,t} + \beta^3\, \beta^1\, \Delta F_{c,t} + \beta^4\, u_{c,t} + u_{s,t}. \tag{3.6}$$

Coefficients β^3 and β^4 respectively quantify how changes in the customer's planned, and unplanned, inventory buffers influence the supplier's ordering decisions. Because the information pertaining to the customer's changes in planned and unplanned inventory is already contained in the supplier's demand, these coefficients represent an explicit over-reaction to such inventory changes. The null hypothesis, that suppliers only respond to downstream inventory changes through the demand information, implies $\beta^3 = \beta^4 = 0$.

3.4 Demand Forecasts

In view of the fact that management's forecasts are not publicly available, we must estimate sales forecasts for every firm in the sample. This poses a challenge because we do not have information regarding the forecasting methods used in practice by the firms, and must thus make a simplifying assumption.

There is a vast body of research that attempts to quantify the performance of different forecasting methods and the subsequent decision on which method to use in different contexts. One well established method to quantify forecast performance is through the so-called forecast competitions: Empirical studies where different forecasting methods are used to forecast a large number of data series in an effort to obtain objective measures of relative performance. Makridakis and Hibon (2000) present the results of one such competition and compare the results with prior competitions. They show that more complex methods do not necessarily exhibit better performance, and that performance itself is dependent of the particular performance measure used. More importantly, they show that these results are consistent across studies.

Taking this into account, as well as the prevalence of seasonal, trending, time series in our data, we compute forecasts for every time series in our sample using the simplest seasonal-forecast method: the additive seasonal Holt-Winters forecasting procedure (Chatfield, 1978). Dekker et al. (2004), in a study aimed at developing methods to improve seasonal forecasts, show that the Holt-Winters method (HW) performs best when seasonality patterns are deterministic, and when demand variance is reduced through aggregation. The temporal and product aggregation present in our data series, combined with the relative simplicity of the HW method motivate its adoption in this study.

The HW forecasting procedure requires three smoothing constants, one each for the level (α), trend (β), and seasonal (γ) components. Formally, given the estimates for the level ($a(t)$), linear trend ($b(t)$), and seasonality ($s(t + \tau - L)$), the τ step-ahead forecast, $\hat{x}_{t+\tau}$, is defined as:

$$\hat{x}_{t+\tau} = (a(t) + b(t)\tau)\, s\,(t + \tau - L)\,, \tag{3.7}$$

where L measures the periodicity of the seasonality ($L = 4$ in quarterly data). Given the smoothing parameters α ($0 \leq \alpha \leq 1$), β ($0 \leq \beta \leq 1$), and γ ($0 \leq \gamma \leq 1$), the updating equations are:

$$a(t) = \alpha \frac{x_t}{s(t-L)} + (1-\alpha)\left(a(t-1) + b(t-1)\right), \tag{3.8}$$

$$b(t) = \beta\left(a(t) - a(t-1)\right) + (1-\beta)b(t-1), \tag{3.9}$$

$$s(t) = \gamma\left(\frac{x_t}{a(t)}\right) + (1-\gamma)s(t-L), \tag{3.10}$$

We compute the forecast for each firm using the same smoothing parameters ($\alpha = \beta = \gamma = 0.3$)[8] .

As an additional robustness check, we performed analyses using different forecasting methods. In particular, we used the time-series data to compute the best-fitting parameters for each individual firm, as well as the best-fitting sales forecasts using simple exponential smoothing and Holt's linear trend forecasting procedures. We calculated the errors for each forecasting method, for each individual series and then performed the entire analysis using the best-fitting forecast per series. The results obtained with the latter method are comparable to the results using only the HW forecasts. Therefore, we report the results obtained using the HW method. By choosing a single method for every firm we avoid introducing unwarranted complexity, as well as potential biases (we have no reason to believe firms use the best-available forecasting method in their operations) into the analysis.

3.5 Econometric Specification

We use fixed-effects OLS estimation with robust standard errors (to account for heteroscedasticity in the data) to estimate the following regression model for customers:

$$\Delta i_{c,t} = a_c + \beta^1\,\Delta F_{c,t} + u_{c,t}, \tag{3.11}$$

where, from the inventory balance equation, we define $\Delta i_{c,t}$ as,

$$\Delta i_{c,t} = i_{c,t} - i_{c,t-1} = q_{c,t} - d_{c,t}. \tag{3.12}$$

Here, a_c is the time-invariant firm-specific fixed effect, β^1 is the coefficient of $\Delta F_{c,t}$, and u_c, t, the unplanned change in inventory buffer, is defined as the error term for the observation.

To test hypotheses 1 and 2, we perform a similar regression on the upstream data. For each customer-supplier pair, c-s, we have:

$$\Delta i_{s,t} = a_s + \beta^2\,\Delta F_{s,t} + r_{c,s}\,\beta^3\,\beta^1\,\Delta F_{c,t} + r_{c,s}\,\beta^4\,u_{c,t} + r_{c,s} + u_{s,t}, \tag{3.13}$$

where $r_{c,s}$ is a moderating variable derived from the relative sizes of the firms, computed through:

$$r_{c,s} = \frac{1}{T}\frac{\sum_1^T d_{s,t}}{\sum_1^T d_{c,t}}, \tag{3.14}$$

[8]We settled on these values after performing an exploratory search on randomly chosen series. We found forecast performance to be quite robust within reasonable parameter values, and $\alpha = \beta = \gamma = 0.3$ to be a good compromise between the nervousness and tracking ability of the forecasts.

with T the length of the link between firms. We include this interaction effect because, by definition, the orders of customer c consist of an unknown fraction of the demand of s. By re-scaling the customer parameters thus, we obtain a more meaningful estimation of the regression coefficients β^3 and β^4. Additionally, we include the coefficient $r_{c,s}$ in the regression to test for any information contained in the scaling coefficient by itself.

4 Safety Stock Model

In this section, we study the unplanned change in inventory buffers in greater detail. We develop a series of hypotheses to study the relationship between the changes in inventory buffers and the economic and financial conjuncture. To test these hypotheses, we adopt the econometric structural modeling framework developed by Olivares et al. (2008) with which we impute the cost parameters of a rational newsvendor-type model to the empirical observations.

Newsvendor-style equations are common in the inventory-modeling literature. They provide a way of quantifying the trade-off between the holding- and penalty-costs that result from over- and under-ordering in a stochastic setting. While the newsvendor formulation depends on strong assumptions (single-item, single-period systems with zero lead time), studies have found that newsvendor-style equations also hold in more complex inventory systems. For example, Rogers and Tsubakitani (1991) prove that a newsvendor-type result minimizes costs in a divergent two-echelon, periodic-review inventory system with positive lead times and budgetary constrains. Further, Diks and De Kok (1998) show that in a divergent *N-echelon* system, applying nesvendor-type equations at every end-stockpoint minimizes long-run costs. In this section, we assume that the determination of the empirical order quantities in our sample follows a rational newsvendor-style model where the critical fractile (determined by the relative cost of over- and under-ordering) varies, period-by-period and firm-by-firm.

In this model, we explicitly link the unplanned changes in the inventory buffers to a cost function (represented by the critical fractile) unknown to us, but known to the decision-maker. In this view, the unplanned change in inventory buffer reflects a hedge made by the decision-maker based upon a cost structure that is no longer assumed constant, but that changes in time. Since this cost information is a priori unknown to us, to estimate it we assume that the decision-maker is rational, and that the decisions he makes, which we can observe in our data, are optimal in the context of this newsvendor-type cost model.

We observe these newsvendor decisions in the form of variable inventory buffers. In the preceding section, we introduced a replenishment model that quantified safety stock changes through two parameters: planned and unplanned changes in the inventory buffers. The former explicitly describes the variation due to a shift in the mean demand (as measured by a change in the firms's forecasts), while the latter acts as an umbrella factor that represents any other possible changes. With our newsvendor-type model, we assume that unplanned changes are driven by changes in the cost factors. After we obtain an estimate of the costs that drive the decisions, we test a series of hypothesis related to the external factors driving these costs.

4.1 Newsvendor Model

Let $C^u_{s,t}$ and $C^o_{s,t}$ represent supplier s's underage and overage costs, respectively, at time t. In the context of our model, because we assume that firms carry safety stocks, we relate these costs to the cost of increasing (or decreasing) the unplanned component of the inventory buffers. This is represented by a cost function dependent on the deviation of orders from the demand plus planned changes in the inventory buffer:

$$C^{UB}(q_{s,t}) = \left[C^o_{s,t}(q_{s,t} - (d_{s,t} + p_{s,t}))^+ + C^u_{s,t}((d_{s,t} + p_{s,t}) - q_{s,t})^+\right], \tag{4.1}$$

where $p_{s,t}$ is the planned change in inventory buffer, and $C^{UB}(q_{s,t})$ the total cost related to changes to the unplanned inventory buffer. Here, we are not interested in assigning a defined interpretation to these costs, rather, we are interested in the relative cost ratio:

$$\gamma_{s,t} = \frac{C^o_{s,t}}{C^u_{s,t}}. \tag{4.2}$$

This cost ratio can vary within a single supplier over time, and it depends on information known by the decision-maker. When $\gamma_{s,t}$ increases, the firm has an incentive to reduce inventories; when $\gamma_{s,t}$ decreases, the firm has an incentive to increase inventories. Assuming continuous variables, the first order condition that follows from a one-period, myopic minimization of the cost Equation 4.1 results in the following condition for the optimal decision $q^*_{s,t}$:

$$F(q^*_{s,t}) = Pr(d_{s,t} + p_{s,t} \leq q^*_{s,t}) = \frac{1}{1 + \gamma_{s,t}}. \tag{4.3}$$

where $d_{s,t} + p_{s,t}$ is the estimated order quantity before considering the cost components and can be estimated from our data through:

$$d_{s,t} + p_{s,t} = a_s + \beta^2\,\Delta F_{s,t} + r_{c,s}\,\beta^3\,\beta^1\,\Delta F_{c,t} + r_{c,s}\,\beta^4\,u_{c,t} + r_{c,s} + \epsilon_{s,t}, \tag{4.4}$$

$$d_{s,t} + p_{s,t} = \Omega X_{s,t} + \epsilon_{s,t}, \tag{4.5}$$

where $\epsilon_{s,t}$ represents the error in the estimation and we use Ω and $X_{s,t}$, vectors of coefficients and covariates, to represent the estimation equation in compact form.

4.2 Hypothesis Development

The reasoning behind the use of a policy through which the decision-maker of a firm is allowed to adjust purchase orders every period, is that there are conditions not captured by the stationary-cost model that, in practice, impact daily decision making. Examples of such conditions are batch-discount pricing, promotions (both at the supplier and customer level), advance information not captured in the forecast, the firms' financial standing, and macro economic conditions. While we cannot model the full extent of information available to a decision maker, we can track certain financial indicators and the overall macro-economic conjuncture. Consequently, we present two hypotheses that link these indicators to the variable cost ratio presented in the previous section.

Our first hypothesis comes as a consequence of results from the literature. Udenio et al. (2012) show that a sharp decrease in target inventories, as a reaction to the onset of the recent financial crisis, is consistent with the dynamics observed by manufacturers in the periods following Lehman Brothers' bankruptcy. In spite of the unusual magnitude and synchronization of the recent financial crisis, the mechanism proposed (that firms reduce target inventory levels when they face financial difficulties) is not new. Escaith et al. (2010), for example, suggest that reducing inventories is a common first reaction in the face of adverse credit conditions and activity slowdown. More recently, Pesch and Hoberg (2013) analyze firms facing financial distress during the 1995-2007 period and estimate that approximately 70% reduce their inventories in order to free up cash and prevent bankruptcy.

Thus, we expect to see a negative relationship between financial constraints and the cost ratio. Given this, we formulate our cost Hypotheses:

H 3 *When firms are constrained by liquidity, they adjust their critical fractile down.*

Similarly, we hypothesize that the overall economic sentiment will have a positive association with the acceptable inventory-related risks that a firm is willing to face; in recessionary times, firms will prioritize cash over service levels. Using the relative change in Gross Domestic Product (GDP) as a proxy to the overall economic conjuncture, we expect that negative GDP changes will shift the cost ratio balance towards penalizing overage. Therefore, we hypothesize that:

H 4 *When macro-economic conditions are adverse (GDP decreases), firms adjust their critical fractile down.*

4.3 Structural Estimation of Cost Ratios

In the standard normative approach to newsvendor-type models, the researcher assumes a distribution function for the random variable and certain explicit cost parameters. With these assumptions, he then computes the optimal ordering decision $q*$. Unfortunately, we cannot directly observe the evolution of the cost ratios for the firms in our dataset. Thus, we use a structural modeling framework to estimate the cost parameters given an assumed distribution and observations of the realized decisions.

We assume that the decision-maker is locally rational and therefore the observed orders are optimal. We use this assumption to impute, for each observation, the cost ratio that would make the observed decision rational.

Additionally, we cannot assume that two firms will react equally given a certain cost ratio. There is an ex ante heterogeneity in the inventory buffers; different decision-makers use different processes to select the target buffer inventory (e.g., at an aggregate level the inventory buffer may be associated to the number of Stock Keeping Units (SKU), the time of year, or other firm-specific factors). To model this heterogeneity in the inventory buffers, we follow Olivares et al. (2008). We assume that the value of the inventory buffer is given by independent random variables from a common family of distributions, $(F(\cdot;\theta) : \theta \in \Theta)$, where θ is a vector parameter from the parameter space Θ which characterizes each member of the class. The distribution of the inventory buffer of supplier s at time t is given by $F(\cdot;\theta_{s,t})$. We let this distribution depend on the vector of covariates $X_{s,t}$ as defined in Equation (4.4), and assume the functional form:

$$\theta_i = h(X_{s,t}, \eta), \tag{4.6}$$

where η is a vector of parameters to be estimated. Thus, the distribution of the desired inventory buffer for firm s at time t, $F(\cdot;\theta_{s,t})$ is characterized by the functional form of the distribution, the function $h(\cdot;\cdot)$, the vector η, and the vector of covariates $X_{s,t}$. In other words, all else being equal, different decision makers will have different target inventory levels in different periods.

In addition, recall that the decision-maker may face different trade-offs between overage and underage costs across observations: the cost ratio γ may differ across observations, and it depends on a series of factors that are a priori unknown to us. Formally, we define:

$$\gamma_{s,t} = g(Z_{s,t}, \alpha), \tag{4.7}$$

where Z_i is a vector of covariates, $g(\cdot)$ is a link function, and α is a vector of parameters to be estimated.

We can express the critical fracile as:

$$F(q_i^*; h(X_{s,t}, \eta)) = \frac{1}{1 + g(Z_i, \alpha)}, \tag{4.8}$$

where q_i^* specifies the optimal decision for each observation.

Following Olivares et al.'s (2008) N1 model of the decision-maker behavior, we assume that there are unobservable factors that affect the calculation of the overage/underage ratio. Let $\xi_{s,t}$ be an i.i.d (unobservable) factor that affects the calculation of cost ratio, $E(\xi_{s,t} = 0)$ and let the cost ratio follow the following log-linear specification:

$$\text{Log}\,(\gamma_{s,t}) = \alpha Z_t + \xi_t. \tag{4.9}$$

Since we do not know the realizations of $\gamma_{s,t}$, we cannot estimate α. We know, however, that if the decision-maker is rational, then she will behave according to the critical fractile:

$$\gamma_{s,t} = \frac{1}{F(q_{s,t};\theta_{s,t})} - 1 \tag{4.10}$$

The procedure to estimate α is then:

Step 1: Estimate η through maximum likelihood using the observed realizations of $q_{s,t}$. Use $\hat{\eta}_{s,t}$ to compute the fitted values $\hat{\theta}_{s,t} = h(X_{s,t}, \hat{\eta})$.

Step 2: Compute the estimated cost ratios $\hat{\gamma}_{s,t} = 1/F(q_{s,t}; \hat{\theta}_{s,t}) - 1$, and then estimate α through an OLS estimation of Equation (4.9).

(Olivares et al., 2008).

We assume that the distribution of the actual orders placed by the supplier at time t (demand plus planned changes in inventory buffer plus unplanned changes in inventory buffer) is defined by the vector $\theta_{s,t} = (\mu_{s,t}, \sigma_{s,t})$ and the orders placed can be written as:

$$q_{s,t} = \Omega X_{s,t} + \epsilon_{s,t}. \tag{4.11}$$

(Olivares et al., 2008) show that, if we assume $\epsilon_{s,t}$ to be i.i.d, normally distributed with mean zero and standard deviation σ, then $\eta = (\Omega, \sigma^2)$, $h(X_{s,t}, \Omega, \sigma^2) = (\Omega X_{s,t}, \sigma^2)$, and estimating (Ω, σ^2) via maximum likelihood is equivalent to estimating Ω through OLS and σ through the standard deviation of the regression residuals. Furthermore, we can estimate the critical fractile through:

$$\begin{aligned} F(d_{s,t} + p_{s,t}, \hat{\theta}_{s,t}) &= \Pr\left(d_{s,t} + p_{s,t} \leq q^*_{s,t}\right) && (4.12) \\ &= \Phi\left(\frac{q_{s,t} - \hat{\Omega} X_{s,t}}{\hat{\sigma}}\right). && (4.13) \end{aligned}$$

And finally estimate $\gamma_{s,t}$ through:

$$\hat{\gamma}_{s,t} = \frac{1}{F(d_{s,t} + p_{s,t}, \hat{\theta}_{s,t})} - 1 \tag{4.14}$$

Since the normality assumption is quite restrictive, we repeated the analysis using the empirical distribution of the regression errors for each industry segment to calculate the critical fractile. Results obtained using said method are consistent with the results derived with this assumption.

4.4 Econometric Specification

We now formulate the econometric specification to test Hypotheses 3 and4. After estimating the cost ratio γ, we obtain an estimate of the vector of coefficients α through:

$$\text{Log}(\gamma_{t,s}) = \lambda^1 \mathit{QuickRatio}_{s,t-1} + \lambda^2 \Delta \mathit{GDP}_{t-1} + \lambda^3 \mathit{Year}_{s,t} + \lambda^4 q_2 + \lambda^5 q_3 + \lambda^6 q_4 + \xi_t. \tag{4.15}$$

Here, $\mathit{QuickRatio}_{s,t-1}$ is the lagged quick ratio of firm s, calculated using the financial identity:

$$\mathit{QuickRatio}_{s,t} = \frac{\mathit{CurrentAssets}_{s,t} - \mathit{Inventories}_{s,t}}{\mathit{CurrentLiabilities}_{s,t}}. \tag{4.16}$$

ΔGDP data is obtained from the Bureau of Economic Analysis[9]. To control for other external effects, we add *Year*, a linear time trend dummy; and q_2–q_4, quarterly dummies.

[9] http://bea.gov/national/index.htm

5 Results

We use the "xtreg" panel data module in STATA to perform our analysis. We estimate fixed effect regressions with robust standard errors.

Table 3 shows the results of the estimation of the inventory model with the change in supplier's inventory as the dependent variable. Column 1 provides the results for the pooled regression; columns 2–4 provide the results for individual industry segments as defined by the 2-digit NAICS industry code. Similarly, Column 1 of Table 4 provides the pooled results of the cost ratio model, with $\text{Log}(\gamma_{s,t})$ as the dependent variable; columns 2–4 show the results for the individual industry segments. Both tables show the estimation results using all periods in the sample. Table 5 shows the detail of the segments included in each of the NAICS codes.

The data at the aggregate level are consistent with Hypothesis 1: Upstream inventory changes are positively with planned changes in downstream inventory buffers. This implies that upstream firms overreact to downstream inventory changes. This relationship is not statistically significant for industries that belong to NAICS code 32.

The data at the aggregate level are consistent with Hypothesis 2: Upstream inventory changes are positively with unplanned changes in downstream inventory buffers. This implies that upstream firms overreact to downstream inventory changes. This relationship is statistically significant for all individual industries.

The data at the aggregate level are consistent with Hypothesis 3: The estimated cost ratio decreases with the lagged quick ratio. This relationship is also not significant for industry code 32.

The data at the aggregate level are consistent with Hypothesis 4: The estimated cost ratio decreases with the lagged change in GDP. However, this effect appears to be driven mainly by firms in industry code 33; this relationship is not significant for industry codes 31 and 32.

To add to the hypotheses tests, we analyze the significance of the other regression coefficients. The inventory regression for the industry code 32 shows that, in addition to the scaled change in downstream buffer, the firm's own change in forecast is not statistically significant. This suggests that this segment does not plan its production runs according to forecasts. A plausible explanation for this observation is that code 32 consists majorly of process industries.

The statistical significance of the dummy variables in the cost ratio regressions are consistent across all industry segments. The 3rd and 4th quarter dummies are statistically significant and positive for all industries; the 2nd quarter dummy is not statistically significant for code 31. Furthermore, the coefficients increase from q_2 to q_4, this reflects a negative association between inventory buffers and the fiscal year cycle—with buffers decreasing until they reach a minimum in the last quarter. The main reason for including the yearly trend in the cost ratio regression was to account for the potential influence that expanding product lines can have in the inventory buffers. However, the yearly trend is statistically significant only in code 32 industries, and with a positive sign. This suggests an increasing trend in the cost ratio, equivalent to a decreasing trend in buffers. Together with the results obtained through the inventory regression results for code 32 industries, these observations merit further analysis.

Table 3 – Pooled and industry-specific inventory regressions for period 1984-2013

Coefficient	Pooled		NAICS 31		NAICS 32		NAICS 33	
ΔF_t	0.055	(0.020)***	0.182	(0.037)***	0.005	(0.025)	0.071	(0.023)***
Scale	0.153	(0.765)	7.949	(4.607)*	-1.210	(1.306)	0.304	(0.530)
Scaled Unplanned Buffer	0.120	(0.032)***	0.206	(0.099)**	0.226	(0.079)***	0.097	(0.033)***
Scaled Planned Buffer	0.446	(0.135)***	0.680	(0.316)**	0.179	(0.191)	0.437	(0.147)***
Constant	1.760	(0.131)***	0.578	(0.344)*	4.059	(0.165)***	1.110	(0.117)***
N	71337		7463		15662		48212	
Suppliers	2558		275		624		1659	

Table 4 – Pooled and industry-specific cost regressions for period 1984-2013

Segment	Pooled		NAICS 31		NAICS 32		NAICS 33	
ΔGDP_{t-1}	-0.011	(0.003)***	0.006	(0.005)	0.006	(0.011)	-0.020	(0.003)***
QuickRatio_{t-1}	-0.005	(0.001)***	-0.065	(0.015)***	-0.001	(0.001)	-0.008	(0.001)***
Scaled Unplanned Buffer	0.001	(0.001)	-0.003	(0.003)	0.000	(0.003)	0.001	(0.001)
Scaled Planned Buffer	-0.004	(0.003)	-0.005	(0.008)	0.002	(0.004)	-0.004	(0.003)
Year	0.001	(0.003)	0.005	(0.005)	0.013	(0.006)**	-0.003	(0.004)
q_2	0.047	(0.015)***	-0.046	(0.059)	0.133	(0.038)***	0.032	(0.016)**
q_3	0.161	(0.019)***	0.360	(0.091)***	0.224	(0.053)***	0.115	(0.019)***
q_4	0.274	(0.026)***	0.399	(0.106)***	0.286	(0.066)***	0.240	(0.026)***
Constant	-0.059	(0.067)	-0.181	(0.142)	-0.404	(0.148)***	0.061	(0.080)
N	70,962		7,441		15,617		47,904	

Note: Standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

5.1 The Impact of the 2008 Financial Collapse

The recent credit crisis was global in nature, dramatic in magnitude, and significantly affected the performance of manufacturing firms (Levchenko et al., 2010). Udenio et al. (2012) argue that pressing financial conditions during the recent financial crisis of 2008 drove individual firms to seek monetary refuge by converting inventories into cash, and find support

Table 5 – Segments per industry code

Code	Industrial Segments
NAICS 31	Food, Beverage and Tobacco, Textile, Apparel, and Leather Manufacturing.
NAICS 32	Wood Product, Paper, Printing, Petroleum and Coal, Chemical, Plastics and Rubber, and Non-metallic Mineral Product Manufacturing
NAICS 33	Primary Metal, Fabricated Metal, Machinery, Computer and Electronic Product, Electrical Equipment, Appliance and Component, Transportation Equipment, Furniture, and Miscellaneous Manufacturing.

support for their hypothesis at the individual supply chain level. Similar observations, concerning higher aggregation levels, have also been made in the financial literature: Gao and Yun (2009), for example, explicitly link manufacturing performance in the periods following Lehman brothers' bankruptcy to firms' ability to withstand the financial turmoil. They show that firms' access to liquidity is positively associated with their business performance during the 2008-2009 period.

The results we have presented thus far in this paper take explicit consideration of financial conditions. To account for the potential impact that significant[10] crisis - related disruptions could have in our results, we temporally disaggregate our dataset and repeat our econometric analysis independently for the 1984–2006 and 2007–2013 periods.

Tables 6 and 7 provide the results of the inventory regressions for the periods 1984–2006 (pre-crisis) and 2007–2013 (crisis/post-crisis) respectively. Similarly, Tables 8 and 9 show the results of the cost ratio regressions for those periods.

The temporally disaggregated data are consistent with the findings detailed in the previous section. All hypotheses are supported by the pooled data.

At the industrial segment level, it is interesting to note that the results from the pre- and post-crisis inventory regressions are generally consistent for codes 32 and 33, but not for code 31. We see, in the pre-crisis period (column 2 of Table 6), no statistical significance for either of the coefficients related to downstream inventory buffers. This changes significantly in column 2 of Table 7.

To test for a change in the behavior of the firms among the periods, we perform a statistical test of the values of the coefficients for pre- and post-crisis regressions. We do so by generating a dummy variable to indicate whether an observation belongs to the pre- or post-crisis period and then re-running the regression with an interaction term between this indicator variable and each of the predictors. Then, the *p-value* for the interaction term effectively gives us a significance test for the difference between the coefficients. We find that, at the aggregate level, the difference between the pre- and post-crisis Scaled Planned Buffer coefficients is statistically significant at the 10% level. None of the other coefficients

[10]As in behavior-changing paradigm shifts.

show a statistical difference across periods.

Comparing the results of the cost ratio regressions, results at the aggregate and industry segment levels are generally consistent. A notable observation is that the quick ratio coefficient for code 32, which was not statistically significant in the previous analysis becomes significant and negative in the post-crisis regression (column 3, Table 9). This suggests that process industries also steered on cash during and after the credit crisis. Also notable is the statistical significance and negative sign of the yearly trend dummy in the pre-crisis regression. This is mainly driven by code 33 (column 3, Table 8) and suggests a progressive increase in the desired inventory buffers through this period. This relationship turns statistically non-significant in the post crisis period. However, further research is needed to identify the causality of the '84-'06 relationship (an increase in the number of SKU's is a plausible explanation), and the reasons why this relationship is not observed in the post-crisis period.

Finally, we perform statistical tests to quantify the change in the coefficients. We find that the quick ratio coefficient during the post-crisis period is more negative than during the pre-crisis period with a statistical significance at the 1% level; the quarterly dummies for 3rd and 4th quarter, on the other hand, are found to increase in the post crisis period with the same level of statistical significance. This underscores the increased importance of the financial performance during the period inasmuch as it highlights an increase in the association between liquidity and inventory buffers, and between the fiscal year and inventory buffers.

Table 6 – Estimation results for period 1984-2006

Segment	Pooled		NAICS 31		NAICS 32		NAICS 33	
ΔF_t	0.0460	(0.0179)**	0.146	(0.0491)***	0.0644	(0.0489)	0.0395	(0.0185)**
Scale	0.0291	(0.742)	0.612	(2.104)	0.731	(0.432)*	0.0200	(0.804)
Scaled Unplanned Buffer	0.0843	(0.0420)**	0.124	(0.0935)	0.0590	(0.0278)**	0.0837	(0.0461)*
Scaled Planned Buffer	0.597	(0.169)***	0.215	(0.407)	0.236	(0.170)	0.627	(0.182)***
Constant	1.029	(0.126)***	-0.0728	(0.146)	2.268	(0.075)***	0.871	(0.151)***
N	51029		5404		9758		35867	
Suppliers	2235		249		502		1484	

Table 7 – Estimation results for period 2007-2013

Segment	Pooled		NAICS 31		NAICS 32		NAICS 33	
ΔF_t	0.0602	(0.0328)*	0.242	(0.0420)***	-0.000183	(0.0229)	0.130	(0.0450)***
Scale	0.292	(1.702)	11.623	(6.684)*	-0.0439	(1.953)	1.613	(0.682)**
Scaled Unplanned Buffer	0.187	(0.0555)***	0.266	(0.113)**	0.341	(0.131)**	0.117	(0.0440)***
Scaled Planned Buffer	0.259	(0.131)**	0.735	(0.300)**	-0.131	(0.354)	0.232	(0.135)*
Constant	3.593	(0.306)***	3.025	(0.677)***	6.517	(0.268)***	1.826	(0.100)***
N	20308		2059		5904		12345	
Suppliers	906		99		274		533	

Note: Standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 8 – Pooled and segment-specific cost regressions for period1984-2006

Segment	Pooled		NAICS 31		NAICS 32		NAICS 33	
ΔGDP$_{t-1}$	-0.007	(0.002)***	0.011	(0.005)**	0.004	(0.003)	-0.014	(0.003)***
QuickRatio$_{t-1}$	-0.003	(0.001)***	-0.041	(0.010)***	0.000	(0.000)	-0.006	(0.001)***
Scaled Unplanned Buffer	0.001	(0.001)	-0.002	(0.002)	-0.001	(0.002)	0.001	(0.001)
Scaled Planned Buffer	-0.001	(0.003)	0.014	(0.009)	0.003	(0.003)	-0.002	(0.003)
Year	-0.004	(0.002)**	-0.000	(0.002)	0.001	(0.003)	-0.006	(0.002)***
q2	0.041	(0.014)***	0.017	(0.042)	0.080	(0.030)***	0.028	(0.016)*
q3	0.106	(0.016)***	0.234	(0.055)***	0.121	(0.038)***	0.080	(0.019)***
q4	0.107	(0.020)***	0.254	(0.055)***	0.134	(0.046)***	0.159	(0.022)***
Constant	0.038	(0.030)	-0.063	(0.054)	-0.133	(0.059)**	0.107	(0.038)***
N	50,745		5,391		9,745		35,609	

Table 9 – Pooled and segment-specific cost regressions for period 2007-2013

Segment	Pooled		NAICS 31		NAICS 32		NAICS 33	
ΔGDP$_{t-1}$	-0.018	(0.007)***	-0.019	(0.011)*	0.009	(0.021)	-0.032	(0.006)***
QuickRatio$_{t-1}$	-0.022	(0.004)***	-0.258	(0.078)***	-0.027	(0.008)***	-0.016	(0.004)***
Scaled Unplanned Buffer	0.000	(0.001)	-0.004	(0.003)	0.002	(0.003)	0.000	(0.002)
Scaled Planned Buffer	-0.005	(0.006)	-0.007	(0.008)	-0.002	(0.006)	-0.005	(0.007)
Year	0.006	(0.010)	0.055	(0.039)	0.012	(0.024)	-0.006	(0.011)
q2	0.036	(0.037)	-0.272	(0.164)*	0.212	(0.075)***	0.014	(0.042)
q3	0.289	(0.046)***	0.632	(0.243)**	0.371	(0.099)***	0.202	(0.043)***
q4	0.515	(0.056)***	0.812	(0.287)***	0.515	(0.106)***	0.443	(0.059)***
Constant	-0.228	(0.298)	-1.503	(1.193)	-0.386	(0.682)	0.120	(0.312)
N	20,217		2,050		5,872		12,295	

Note: Standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

6 Conclusions

In this paper, we have studied the effect of changes of downstream inventories in the production decisions made upstream. We found support for the hypothesis that planned and unplanned changes in a customer's inventory trigger an overreaction on the part of its supplier. Furthermore, we also found support for the hypothesis that decision makers adjust their safety stock (and thus the unplanned component of their inventory changes) according to the economic sentiment (measured by the change in the GDP) and their financial position (measured as the quick ratio).

To study the relationship between downstream and upstream companies, we constructed a database of customer/supplier pairs by taking advantage of a US regulation in which customers that account for at least 10% of a firms' sales must be included in financial reports. This kind of database is not, however, in widespread use because of the format in which the customer names are reported: Rather than reporting a unique and predefined identifier, firms report their customers' names in the form of a plain text string. This causes difficulties for the researcher constructing links from this information, for the data is plagued with spelling mistakes, abbreviations, and unconventional spellings. We overcame this ambiguity in the reporting using a combination of a partial string matching algorithm and manual matching. Our database consists of financial information of supplier-customer pairs during approximately 80000 firm-quarters, in the period 1984-2013.

To test our first set of hypotheses, we derived an econometric specification model that allowed us to separate between the customer's planned and unplanned inventory changes by assuming that planned inventory changes follow the firms' forecast and the unplanned changes depend on factors that we are unable to observe. We found that suppliers consistently overreact to the inventory changes of their customers. This suggests that inventories are being used systematically as drivers of ordering decisions.

The second part of our study expands on this finding with a structural model of the decision making mechanism. In this model, the decision maker is assumed to be following a rational, newsvendor-like policy in a multi-period setting. In this policy, the decision maker adjusts the safety stock component every period following variations of the cost ratio (the ratio between the overage and underage cost). With this model, we found support for the second set of hypotheses. Moreover, and in line with the findings from the literature, we showed that the relative importance of the firm's liquidity as a driver increased in the period 2007-2013 as compared to the 1984-2006 period.

Our study has several limitations. The use of aggregated financial data from Compustat can lead to space and time aggregation biases. We also use proxies that may introduce biases: sales for demand and production for orders. In the structural estimation, we assume a rational decision maker, which assumes knowledge and application of optimal policies. The construction of the supplier/customer pairs also brings limitations. The sample is biased towards large customers and small suppliers, which can potentially cause an over-estimation of the effects that downstream changes have upstream. Even though we control for the size bias within our sample (see the appendix), we cannot discard the possibility that this bias is affecting the sample itself.

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The Influence of firm size bias In §2.1 we observed that, due to the nature of the reporting process, our customer-supplier pair database is biased towards large customers and small suppliers. This bias can potentially affect the generality of our results. It is possible that smaller firms behave differently from larger firms. Smaller firms can be more agile in implementing changes, as well as more sensitive to changes in their liquidity.

To test whether the results obtained from our analysis are being driven primarily by this bias towards smaller suppliers, we partition our data according to the relative size of customer-supplier pairs and repeat our analysis on a sub-sample of our data, comprised of the top 25th percentile. We present the results in tables 10 through 15.

We see that qualitatively, the results obtained with this sub-sample are consistent with those obtained through the analysis of the entire dataset. This suggests that the firm size bias is not driving our results and thus increases the confidence on the results. However, it is important to note that while this rules out the influence of firm size bias in our dataset, it is not a stringent test of the influence of firm size.

Table 10 – Estimation results for period 1984-2013

Segment	Pooled		NAICS 31		NAICS 32		NAICS 33	
ΔF_t	0.053	0.026**	0.236	0.070***	-0.014	0.024	0.090	0.029***
Scale	-0.009	0.895	7.567	4.875	-1.957	1.379	0.197	0.549
Scaled Unplanned Buffer	0.120	0.034***	0.225	0.112**	0.241	0.084***	0.095	0.034***
Scaled Planned Buffer	0.440	0.137***	0.651	0.360*	0.133	0.202	0.420	0.145***
Constant	4.388	0.512***	3.577	1.390**	10.297	0.515***	2.757	0.362***
N	17,757		1,602		3,248		12,907	

Table 11 – Estimation results for period 1984-2006

Segment	Pooled		NAICS 31		NAICS 32		NAICS 33	
ΔF_t	0.061	0.029**	0.141	0.061**	0.038	0.077	0.059	0.030*
Scale	0.017	0.779	1.118	2.974	0.915	0.423**	-0.023	0.835
Scaled Unplanned Buffer	0.087	0.045*	0.163	0.104	0.067	0.027**	0.085	0.049*
Scaled Planned Buffer	0.583	0.165***	0.023	0.496	0.251	0.174	0.610	0.176***
Constant	2.422	0.449***	0.789	0.742	3.584	0.188***	2.323	0.545***
N	11,727		1,023		1,980		8,724	

Table 12 – Estimation results for period 2006-2013

Segment	Pooled		NAICS 31		NAICS 32		NAICS 33	
ΔF_t	0.045	0.034	0.379	0.085***	-0.012	0.024	0.123	0.047***
Scale	-0.292	2.035	9.529	5.203*	-0.728	2.114	1.573	0.687**
Scaled Unplanned Buffer	0.182	0.058***	0.277	0.128**	0.366	0.143**	0.110	0.044**
Scaled Planned Buffer	0.260	0.135*	0.708	0.346**	-0.247	0.370	0.232	0.138*
Constant	8.080	1.059***	10.124	1.719***	18.004	0.813***	3.494	0.249***
N	6,030		579		1,268		4,183	

Note: Standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 13 – Pooled and segment-specific cost regressions for period 1984-2013

Segment	Pooled		NAICS 31		NAICS 32		NAICS 33	
ΔGDP_{t-1}	-0.045	(0.019)**	-0.001	(0.020)	0.005	(0.066)	-0.065	(0.020)***
QuickRatio_{t-1}	-0.011	(0.005)**	-0.323	(0.161)**	-0.000	(0.003)	-0.024	(0.011)**
Scaled Unplanned Buffer	0.001	(0.001)	-0.003	(0.003)	0.001	(0.003)	0.001	(0.001)
Scaled Planned Buffer	-0.000	(0.003)	-0.003	(0.012)	0.003	(0.005)	0.000	(0.003)
Year	0.010	(0.011)	0.006	(0.027)	0.050	(0.037)	0.005	(0.012)
q2	0.137	(0.075)*	-0.179	(0.259)	0.437	(0.189)**	0.115	(0.086)
q3	0.429	(0.102)***	0.744	(0.396)*	0.694	(0.285)**	0.342	(0.112)***
q4	0.782	(0.127)***	0.823	(0.500)	1.024	(0.346)***	0.696	(0.138)***
Constant	-0.292	(0.264)	-0.071	(0.943)	-1.344	(0.954)	-0.079	(0.284)
N	17,503		1,593		3,216		12,694	

Table 14 – Pooled and segment-specific cost regressions for period 1984-2006

Segment	Pooled		NAICS 31		NAICS 32		NAICS 33	
ΔGDP_{t-1}	-0.046	(0.020)**	0.039	(0.020)*	0.011	(0.014)	-0.057	(0.026)**
QuickRatio_{t-1}	-0.009	(0.005)*	-0.224	(0.096)**	0.001	(0.001)	-0.017	(0.011)
Scaled Unplanned Buffer	0.001	(0.001)	-0.002	(0.002)	-0.001	(0.002)	0.001	(0.001)
Scaled Planned Buffer	0.000	(0.003)	0.017	(0.012)	0.004	(0.004)	0.001	(0.002)
Year	0.010	(0.011)	-0.014	(0.009)	0.011	(0.012)	-0.007	(0.013)
q2	0.169	(0.076)**	-0.019	(0.205)	0.231	(0.164)	0.114	(0.086)
q3	0.412	(0.102)***	0.306	(0.189)	0.353	(0.210)*	0.238	(0.113)**
q4	0.739	(0.123)***	0.406	(0.255)	0.508	(0.226)**	0.505	(0.149)***
Constant	-0.259	(0.266)	0.287	(0.310)	-0.531	(0.307)*	0.174	(0.240)
N	16,930		1,020		1,974		8,554	

Note: Standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 15 – Pooled and segment-specific cost regressions for period 1984-2013

Segment	Pooled		NAICS 31		NAICS 32		NAICS 33	
ΔGDP_{t-1}	-0.048	(0.020)**	-0.089	(0.034)**	0.017	(0.125)	-0.081	(0.023)***
$QuickRatio_{t-1}$	-0.010	(0.005)*	-0.623	(0.613)	-0.139	(0.112)	-0.060	(0.031)**
Scaled Unplanned Buffer	0.001	(0.001)	-0.004	(0.003)	0.003	(0.003)	0.001	(0.001)
Scaled Planned Buffer	-0.000	(0.003)	-0.003	(0.012)	-0.001	(0.007)	-0.001	(0.006)
Year	0.010	(0.011)	0.126	(0.169)	0.019	(0.162)	-0.007	(0.034)
q2	0.139	(0.078)*	-0.661	(0.517)	0.698	(0.439)	0.022	(0.165)
q3	0.433	(0.108) ***	1.447	(1.003)	1.109	(0.632)*	0.510	(0.210)**
q4	0.801	(0.130)***	1.734	(1.060)	1.716	(0.560)*	1.003	(0.216)***
Constant	-0.290	(0.276)	-3.303	(5.778)	-0.343	(4.555)	0.163	(0.985)
N	16,483		573		1,242		4,140	

Note: Standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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