Cash-Flow Bullwhip Effect in the Semiconductor Industry: An Empirical Investigation

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Abstract. Cash flow bullwhip effect (CFB) is the amplification of working capital variance along a supply chain. High CFB is a sign of inefficient working capital (WC) management and can lead to a significant reduction in financial resilience. CFB can be used as a measure of a company's ability to manage operational risks and corresponding resilience. We investigate the existence of CFB and the traditional bullwhip effect (BWE) in a sample of 238 semiconductor companies over 2010-Q1 to 2020-Q4. These companies' average CFB and BWE are 3.95 and 2.77, respectively. We find that CFB and BWE of a semiconductor company are negatively associated with company size, degree of seasonality in demand, and company's payment policy conservativeness; and positively associated with procurement and payment lead times.

Keywords: Bullwhip Effect, Working Capital, Supply Chain, Cash flow.

1 Introduction

Working capital (WC) and cash conversion cycle (CCC) are important financial metrics for supply chains. Inefficient management of WC and CCC can lead to insolvency and can increase the risk of bankruptcy [1]. Numerous attempts have been made from a supply chain perspective on studying WC and CCC (e.g. [2–4]).

Hofmann and Kotzab [2] built a conceptual model of a supply chain to study the effect of inventory management, optimization of payment period, and collaboration between supply chain partners on the CCC of supply chain entities. Peng and Zhou [3] studied the effect of speed of cash turnover and discount rates on profitability in a two-echelon supply chain. Pirtila et al. [4] performed an empirical analysis of WC management in the Russian automotive industry. They showed that firms in the Russian automotive industry do not manage WC in a collaborative manner. None of these studies has in any manner focused on WC variance propagation in supply chains.

WC and CCC variance propagations in supply chains remain poorly studied by the scientific community [5]. Such studies could be especially critical for the semiconductor industry, where lead times are long, investments are huge, raw material supplies are tight, and working capital requirements are large.

Supply chains experience two kinds of risks: Operational and Disruption risks [6]. Bullwhip effect (BWE), the amplification of material flow variability in a supply chain, is a measure of how well a supply chain manages its operational risks. On the other hand, the ability to recover from disruptions is measured by resilience. Dominguez et al. [7] showed that BWE avoidance increases a supply chain's resilience.

BWE has received significant attention in the literature [8]. However, this is not the case for cash flow bullwhip in supply chains [5]. Cash flow bullwhip was originally characterized by Tangsucheeva and Prabhu [1] as the ratio of variance in a supply chain entity's CCC to the variance of its demand. Henceforth, we refer to Tangsucheeva and Prabhu's [1] definition of cashflow bullwhip as CFB-TP. Mathematical formulation of a supply chain entity's CFB-TP is given as follows.

$$CFB\text{-}TP = \frac{var(CCC)}{var(Demand)} \tag{1}$$

A caveat in the formulation of CFB-TP is that CCC is measured in number of days, whereas Demand is measured in dollars. Since CFB-TP represents the ratio of variance of 2 different units of measurement, it cannot be used to check if financial variances are either attenuating or amplifying across a supply chain. To overcome this shortcoming, Patil and Prabhu [9] redefined cashflow bullwhip (henceforth CFB) as the amplification of working capital variance across supply chain entities. CFB is characterized as the ratio of WC variance to Demand variance. Like BWE avoidance increases resilience, it is likely that CFB avoidance increases financial resilience. Mathematical formulations of CFB and BWE are given as follows.

$$\begin{aligned} CFB &= \frac{var(WC)}{var(Demand)} \\ &= \frac{var(Inventory + Cash + Trade\ Receivables - \ Trade\ Payables)}{var(Demand)} \end{aligned} \tag{2}$$

CFB larger than 1 is indicative of a company not managing its WC efficiently. Our objective in this paper is twofold: (i) measure the CFB and BWE experienced by companies in the semiconductor industry, and (ii) examine the association of company-level variables like company size, lead-time, payment policy, liquidity ratio, demand seasonality, demand autocorrelation with CFB and BWE. To the best of our knowledge, this is the first paper that empirically (i) examines the existence of CFB in a supply chain of any kind, and (ii) identifies the company-level variables that probably drive CFB.

2 Data

Public companies in the U.S. are obligated to release quarterly financial data. We access these data between 2010-Q1 and 2020-Q4 for manufacturers in the semiconductor industry (North American Industry Classification System (NAICS) codes 33242, 334413, 334111-334118, 334210-334290) from the Compustat database. Companies with missing values in cost of goods sold (COGS), cash, trade payables, trade receivables, and inventory; and with data series smaller than ten calendar quarters are dropped from the sample. We end up with 238 unique companies in our sample. Compustat database does not report companies' demand series. Therefore, we use each company's COGS series as a proxy for the demand series. As seen in Equations (2) and (3), calculations of a company's CFB and BWE require WC series and Order Quantity series. WC for company i in period t is given as follows.

$$\mathrm{WC}_{i,t} = Cash_{i,t} + Invt_{i,t} + TR_{i,t} - TP_{i,t} \quad (4)$$

where $Casht_{i,t}$, $Invt_{i,t}$, $TR_{i,t}$, and $TP_{i,t}$ are the cash position, inventory, trade receivables, and trade payables of company *i* in period *t*, respectively. Compustat does not report the order quantity series for companies. Therefore, we use a measure called Purchases as a proxy for order quantity. Purchases of company *i* in period t is given as follows.

$$\mathrm{Purchases}_{i,t} = COGS_{i,t} + Invt_{i,t} - \ Invt_{i,t-1} \quad (5)$$

where $COGS_{i,t}$ is the cost of goods sold by company *i* in period *t*.

The WC, Purchases, and COGS series for each company are first-differenced. This operation detrends the data series. Detrending is critical because each company's data series span over 4 – 11 years (10 – 44 quarters), and this is a long enough duration for data series to exhibit stochastic trends. Our objective is to capture WC, Purchases, and COGS series' variances about stochastic trends, not the overall data series variances.

3 Measures and Hypotheses

CFB for company i is determined by substituting its WC and COGS series in Equation (2)'s numerator and denominator, respectively. Similarly, BWE for company i, is calculated by substituting its Purchases and COGS series in Equation (3)'s numerator and denominator, respectively.

We develop several hypotheses to identify the drivers of bullwhip effects (CFB and BWE) in semiconductor industry. These hypotheses on the association of CFB and BWE with company-level variables are based on (i) the analytical model of CFB by Patil & Prabhu [9], and BWE by Chen et al. [10]; and (ii) intuition originating from our knowledge of supply chain literature.

CFB has been shown to be associated with supply chain entity's (or company's) procurement lead time, payment lead time, payment policy conservativeness, demand autocorrelation, and supply chain stage by Patil and Prabhu [9]. On the other hand, BWE has been shown to be associated with lead time, demand autocorrelation, and supply chain stage by Chen et al. [10]; and additionally, with supply chain entity (or company) size, and seasonality ratio by Cachon et al. [11]. Our intuition suggests that since liquidity is important in keeping semiconductor supply chain operations running, liquidity ratio also is associated with CFB and BWE experienced by semiconductor companies. Therefore, we study the association of CFB and BWE with company variables like: company size, liquidity ratio, demand seasonality, procurement and payment lead times, payment policy conservativeness, demand autocorrelation, and supply chain stage. The reader should note that we do not claim that the aforementioned company variables constitute an exhaustive set of variables associated with CFB and BWE. Next, we discuss our hypotheses on the nature of association of the abovementioned company-level factors on CFB and BWE.

Intuition suggests that large semiconductor companies might have smaller inventory variance than smaller companies because the former can aggregate inventories across multiple products and can leverage the concept of vendor-managed inventory (VMI). VMI can allow larger companies to push inventory fluctuations onto their suppliers. Large companies also tend to enforce short payment terms on customers and extended payment terms on their suppliers [2], thereby pushing cash flow risks onto their supply chain partners. Therefore, we hypothesize the following.

Hypothesis 1: CFB and BWE are negatively associated with semiconductor company size.

The mean value of a company's COGS over 2010-Q1 to 2020-Q4 is used as a proxy for a company's size.

Semiconductor supply chains are capital intensive [12, 13] because they need to upgrade processes continuously. Therefore, semiconductor companies require high liquidity to operate efficiently. The need to maintain high liquidity can motivate companies to push cash flow uncertainties onto supply chain partners. Therefore, we hypothesize the following.

Hypothesis 2: CFB is negatively associated with semiconductor company’s liquidity ratios.

The liquidity ratio of company *i* is given as follows.

$$LR_i = \frac{mean(Cash_i)}{mean(Invt_i)} \tag{6}$$

where $Cash_i$ and $Invt_i$ are the cash and inventory series of company *i*.

COGS series of companies in the sample indicate that semiconductor companies experience seasonality in COGS. Given the capital-intensive nature of semiconductor industry, we believe companies have the motivation to smooth their purchases and WC, even more so when demand seasonality exists. Cachon et al. [11] found this to be the case across 74 industries in the U.S. economy. Therefore, we hypothesize the following.

Hypothesis 3: CFB and BWE are positively associated with demand seasonality.

To measure seasonality in demand experienced by a company, we use the seasonality ratio. Seasonality ratio for company *i* is given as follows.

$$SR_i = \frac{Var(COGS_i) - Var(Seasonally\ adjusted\ COGS_i)}{Var(COGS_i)} \quad (7)$$

where, $COGS_i$ is the COGS series of company i and $Seasonally\ adjusted\ COGS_i$ is the deseasonalized $COGS_i$ series. Method described in [14] is used to deseasonalize $COGS_i$ series.

Chen et al. [10] show that BWE is increasing in procurement lead time. Parallelly, Patil & Prabhu [9] show that CFB is increasing in procurement and payment lead times. Therefore, we hypothesis the following.

Hypothesis 4: CFB and BWE are positively associated with semiconductor company's procurement and payment lead times**.**

Procurement and payment lead times are not reported in the Compustat database. Therefore, we use Days Payable Outstanding (DPO) as a proxy for the sum of procurement and payment lead times, LT. DPO for company *i* is given as follows.

$$LT_i = DPO_i = \frac{365}{4 \times \frac{mean(COGS_i)}{mean(TP_i)}} \quad (8)$$

where, TP_i is the trade payables series of company *i*.

Patil & Prabhu [9] show that a supply chain entity's payment policy not only affects its own CFB but also entire upstream supply chain's CFB. Specifically, they show that the more conservative a company's payment policy, the higher the CFB it experiences. Therefore, we hypothesize the following.

Hypothesis 5: CFB is positively associated with a semiconductor company's payment policy's conservativeness.

Company *i*'s payment policy conservativeness is measured by its payment policy parameter which is given as follows.

$$\alpha_i = \frac{mean(TP_i)}{mean(TR_i)} \quad (9)$$

where TP_i and TR_i are the trade payables and trade receivables series of company *i*. Higher the α_i, the more conservative company i's payment policy.

Chen et al. [10] show that a supply chain entity experiences BWE greater than 1 when the entity's demand autocorrelation (ϕ) is greater than 0. We find that, out of the 238 companies in the sample, 234 have demand (COGS) autocorrelation greater than 0. Patil & Prabhu [9] show that for $\phi > 0$, CFB is increasing in ϕ as the latter approaches $\phi_{treshold}$. For $\phi > \phi_{treshold}$, CFB is decreasing in ϕ. Patil & Prabhu [9] find $\phi_{treshold}$ to be greater than 0.75 in all the cases that they explore. Therefore, we hypothesize the following.

Hypothesis 6: CFB and BWE experienced by semiconductor companies are positively associated with demand autocorrelation.

Patil & Prabhu [9] and Chen et al. [10] analytically show that CFB and BWE experienced by upstream supply chain companies are larger than their downstream counterparts. Checking the prevalence of these effects in semiconductor supply chain would require complete knowledge of the upstream and downstream supply chain partners of all the companies in our sample. This is beyond the scope of the present paper. However, we can use the NAICS codes of companies in the sample to classify them into the following categories: (i) Semiconductor Machinery Manufacturing (SMM), (ii) Semiconductor and Related Devices Manufacturing (SRDM), and (iii) Computer and Communications Manufacturing (CCM). These three categories could be assumed to form a notional semiconductor supply chain shown in Fig. 1. Assuming these three categories relate to different stages of the semiconductor supply chain, we hypothesis the following.

Hypothesis 7. The differences in the mean CFBs and BWEs experienced by SMM, SRDM, and CCM companies are statistically significant.

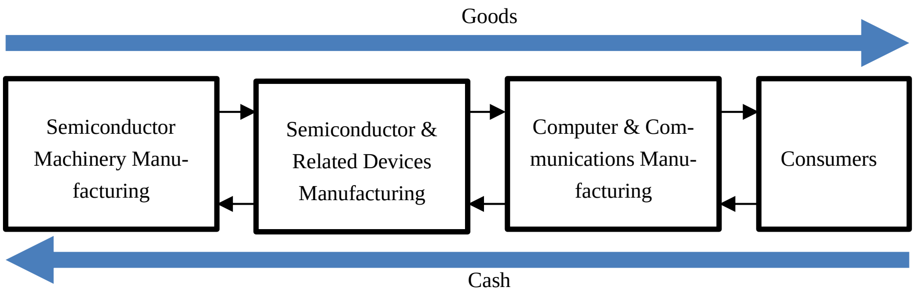

Fig. 1. Model of semiconductor supply chain structure studied in the paper

4 Analysis

In this section, we first quantify the CFB and BWE experienced by companies in the semiconductor industry and then investigate the association of company-level variables with CBF and BWE.

4.1 Existence of CFB and BWE in the semiconductor industry

Based on NAICS codes, the 238 semiconductor companies in the sample belong to eight different sub-industries. Table 1 reports the average and standard deviation of CFB and BWE experienced by these eight sub-industries. All semiconductor sub-industries but Electronic Computer Manufacturing, on average, experience CFB and BWE greater than 1. This shows that CFB and BWE exist in the semiconductor industry. The Telephone Apparatus Manufacturing industry, on average, experiences the largest CFB (5.27), and the Semiconductor & Related Device Manufacturing industry, on average, experiences the largest BWE (3.32).

To check if COVID-19 related supply chain disruptions had any effect on CFB and BWE experienced by semiconductor companies, we performed a t-test on the mean CFB (and BWE) experienced by semiconductor companies over the periods: 2010-Q1 to 2019-Q4 and 2010-Q1 to 2020-Q4. The test fails to reject the null hypothesis that the mean CFB (and BWE) of the 2 populations are the same. Therefore, based on the data we have, we infer that the COVID-19 related disruption did not have significant effect on the CFB and BWE experienced by the semiconductor supply chain. However, it should be noted that our analysis is based on quarterly data which does not provide the temporal granularity that monthly data would. Monthly data might be able to capture the real effect of COVID-19 related disruptions on the CFB and BWE experienced by the semiconductor industry.

Table 1. CFB and BWE experienced by sub-industries in the semiconductor industry.

Sub-industry	CFB		BWE	
	Mean	Std. dev	Mean	Std. dev
Semiconductor Machinery Manufacturing	2.89	2.98	2.98	4.86
Electronic Computer Manufacturing	0.93	0.66	1.12	1.26
Computer Storage Device Manufacturing	3.00	3.81	1.98	1.33
Computer Terminal & Other Computer Peripheral Equipment Manufacturing	4.90	8.06	2.85	2.68
Telephone Apparatus Manufacturing	5.27	4.72	2.60	1.44
Radio & Television Broadcasting & Wireless Communications Equipment Manufacturing	2.73	3.46	2.02	1.86
Other Communications Equipment Manufacturing	2.67	2.35	1.41	0.94
Semiconductor & Related Device Manufacturing	4.27	4.71	3.32	3.90

4.2 Association of CFB and BWE with company-level variables

To find the association of CFB and BWE with company variables, we test the hypotheses discussed in Section 3. To test these hypotheses, we build multiplicative regression models of the following types.

$$\log(CFB_i) = a + b_1 \log(size_i) + b_2 \log(LR_i) + \mathrm{b}_3\log(SR_i) + \mathrm{b}_4\log(LT_i) + \mathrm{b}_5\log(\alpha_i) + \mathrm{b}_6\log(\phi_i) + c_1 SMM_i + c_2 SRDM_i + \epsilon_i \tag{10}$$

$$\log(BWE_i) = a + b_1 \log(size_i) + b_2 \log(LR_i) + \mathrm{b}_3\log(SR_i) + \mathrm{b}_4\log(LT_i) + \mathrm{b}_5\log(\alpha_i) + \mathrm{b}_6\log(\phi_i) + c_1 SMM_i + c_2 SRDM_i + \epsilon_i \tag{11}$$

where, b_j for $j \in \{1,2, \ldots ,6\}$ are the regression coefficients of the continuous variables and c_j for $j \in \{1,2\}$ are the regression coefficients of dummy variables SMM_i and $SRDM_i$. To avoid the dummy variable trap, we use $3 - 1 = 2$ dummy variables to represent the 3 supply chain stages (SMM, SRDM, and CCM). For a company that is an SMM, $c_1 = 1$ and $c_2 = 0$. For a company that is an SRDM, $c_1 = 0$ and $c_2 = 1$. Finally, for a company that is a CMM, $c_1 = 0$ and $c_2 = 0$. Only 2 dummy variables are sufficient to indicate if company i is an SMM, SRDM, or a CCM company. ϵ_i additively includes company-specific effects and random noise in the model.

We use multiplicative regression models instead of additive regression models for two reasons: (i) plotting CFB and BWE against $size$, LR, SR, LT, α, and ϕ suggests a log-linear relationship between the variables, and (ii) multiplicative regression models have better explanatory power than additive regression models over our sample of semiconductor companies. The regression models are fit over winsorized data. Winsorizing the top and bottom 1% data dampens the effect of significant outliers. Table 2 reports the regression coefficients of models presented in Equations (10) and (11).

Table 2. Regression model summary

	log(CFB)	log(BWE)
SMM	-0.2	-0.06
SRDM	-3.65***	0.34***
log(size)	-0.09**	-0.06**
log(LR)	0.09	-0.01
log(SR)	-0.06**	-0.05**
log(LT)	0.9***	0.35*
log(α)	-1.32***	-0.38**
Log(ϕ)	0.25	0.34**
Adjusted R-squared (%)	35.2%	13.6%
F-statistic	17.11***	5.66***
N	238	238

***, **, and *denote statistical significance for p-value < 0.001, 0.01, and 0.05, respectively.

The R-squared values of the log(CFB) and log(BWE) models reported in Table 2 are low (35.2% and 13.6%, respectively), but it should be noted that this is an econometric study and therefore is not concerned with the models' predictive powers. The sole objective of these regression models is to make inferences about the association of company-level variables with CFB and BWE. Therefore, low R-squared values are not of much concern here. Results in Table 2 support Hypotheses 1, 3, and 4. The coefficients of company size, seasonality ratio (SR), and procurement + payment lead time (LT) are statistically significant for the models presented in Equations (10) and (11). Contrary to Hypothesis 5, results indicate that the payment policy parameter is negatively associated with CFB and BWE. The more conservative the company's payment policy, the smaller are its CFB and BWE. Hypothesis 6 is only supported for log(BWE). Hypothesis 7 is not entirely supported by the results. Dummy variable SRDM's coefficient is found to be statistically significant. However, the dummy variable SMM's coefficient is not statistically significant. It means that the differences in the mean values of bullwhip effects (CFB and BWE) experienced by SRDM and CMM are statistically significant.

In Table 2, we see that a 1% increase in company size is, on average, associated with a 0.09% and 0.06% drop in CFB and BWE, respectively. 1% increase in seasonality ratio is, on average, associated with a 0.06% and 0.05% drop in CFB and BWE, respectively. 1% increase in lead time is, on average, associated with a 0.9% and 0.35% rise in CFB and BWE, respectively. 1% increase in payment policy parameter is, on average, associated with a 1.32% and 0.38% drop in CFB and BWE, respectively. 1% rise in demand autocorrelation is, on average, associated with a 0.34% rise in BWE.

5 Conclusion

This paper is a step in the direction of empirically investigating the existence of CFB in supply chains. Our results indicate that semiconductor companies experience financial and operational risks in the form of CFB and BWE. These effects experienced by semiconductor companies are associated with company size, lead-time, payment policy, liquidity ratio, demand seasonality, and demand autocorrelation. We also observe the CFB experienced by SRDM companies to be smaller than that by CMM companies, and BWE experienced by SRDM companies to be larger than that by CMM companies.

Future research should focus on analyzing the relationship between CFB and financial resilience, and test if CFB reducing strategies increase financial resilience. It would be remiss of us not to list the limitations of this work. Our sample consists of only those companies which were public for more than ten quarters between 2010-Q1 and 2020-Q4. Therefore, our sample is vulnerable to size bias and survivorship bias. Another limitation of this paper is that it uses imperfect proxies for demand, order quantity, and lead times. Future explorations should investigate the prevalence of CFB across all major industries using better proxies for demand, order quantity, and lead times.

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