Mirroring Payment Terms and Lead Times

by

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ABSTRACT

In a simple representation of a supply chain, products flow from suppliers to customers, and currency flows from customers to suppliers. The period it takes a supplier to satisfy a customer order is called lead time. The period it takes a customer to pay a supplier for product is called payment term. The question this thesis will answer is: Can payment terms be used to offset lead times? Three frameworks are developed in this thesis to quantify the payment term required to offset lead times: the Pipeline and Safety Stock Inventory Offset Framework, On Hand Inventory Offset Framework, and the On Hand Inventory and Ordering Cost Offset Framework. All three build upon the commonly used total cost equation. Empirical analysis of annual reports submitted to the United States Securities and Exchange Commission in 2019 observed a relationship between payment terms and lead times. This thesis makes two contributions to the supply chain literature. First, the total cost equation is updated to differentiate between components of lead time as well as incorporate payment terms. Second, the observation that there is a relationship between payment terms and lead times provides a starting point for future research.

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Table of Contents

List of Figures and Tables

1. Introduction

In 1748, Benjamin Franklin wrote: "Remember that time is money."[1] When he gave that advice to a young tradesman in the 18th century, he probably did not realize it could be applied to inventory management centuries later. In supply chain management theory, the longer lead times are, the higher safety stock and pipeline inventory must be. This time lag requires more cash to be unavailable for other projects. One source of cash to offset higher inventory can be delayed payments to the vendors with long lead times. The question this thesis seeks to answer is: Can payment terms be used to offset lead times?

The two major sections of this thesis are directed at two specific audiences: Supply chain practitioners and corporate executives. For supply chain practitioners, whose day-to-day activities involve supplier negotiation and inventory planning, a framework is provided to understand tactically how working capital can be protected from supplier lead time proposals (see Chapter 3). For corporate executives, who oversee the supply chain organization as one among many functions, an empirical study of corporate financial statements will show lower lead time seem to be related to faster payment collection from customers (see Chapters 4 and 5). Either audience will find that lead times have a direct impact on the financial performance of a firm.

The financial performance of manufacturers is measured by (1) the time it takes to collect from customers, (2) the time inventory remains on hand, and (3) the time it takes to pay vendors. Respectively, these three measures are formally known as days of sales outstanding (DSO), days of inventory on hand (DIO), and days of payables outstanding (DPO). The cash conversion cycle

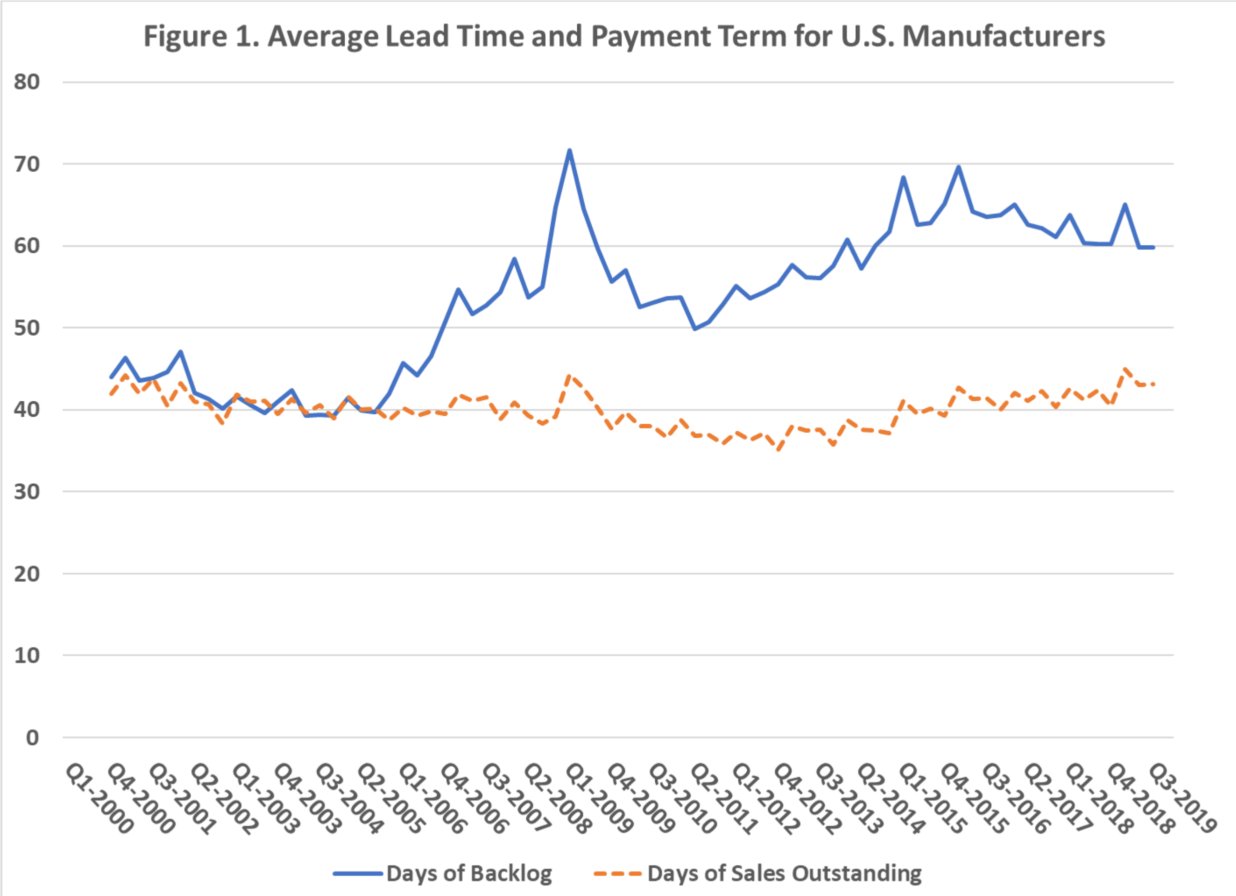
[1] Labaree, Leonard W. (ed.) *The Papers of Benjamin Franklin,* vol. 3, *January 1, 1745, through June 30, 1750*, New Haven: Yale University Press, 1961, pp. 304–308.

is calculated by adding DSO to DIO and subtracting DPO. With other conditions remaining the same, a shorter cash conversion cycle is better than a longer one.

DSO can be calculated by dividing a firm's accounts receivable by annual sales and multiplying by 365 days in a year. DIO can be calculated by dividing a firm's inventory by annual cost of goods sold (COGS) and multiplying by 365 days in a year. DPO can be calculated by dividing a firm's accounts payable by annual COGS. (Alternatively, quarterly sales and COGS can be used, and the resulting number is multiplied by 91 days in a quarter.) One firm's accounts receivable are another firm's accounts payable.

The average length of time it takes for a firm to deliver products to customers can be measured several ways. One way is to divide open orders by annual sales volume and multiply by 365 days in a year. Another way is to estimate the amount of time it takes a firm to convert raw materials into finished goods, known as the "raw-and-in-process (RIP) ratio." The RIP ratio can be determined by adding raw materials to work-in-process inventory, then dividing by COGS and multiplying by 365 days in a year. Some firms publicly disclose backlog and components of inventory (finished goods, work-in-process, and raw materials), so days of backlog and the RIP ratio can be calculated from financial statements. Chapters 4 and 5 will show that firms appear to either have longer DSO and longer days of backlog or shorter DSO and shorter days of backlog.

As of this writing (in 2020), in the United States it takes longer for manufacturers to fulfill orders than it takes for them to collect from customers. (Figure 1) However, this was not always the case, and recent trends indicate these numbers might revert to parity. If that happens, over one trillion dollars of working capital will shift from U.S. manufacturers to their customers.



In the fourth quarter of 2000, when the U.S. Census Bureau first published data on unfilled orders, trade receivables, and sales for U.S. manufacturers, average lead time and average payment term were basically at parity.[2] Unfilled orders were approximately 44 days of sales (a measurement of lead time) and trade receivables were approximately 42 days of sales (a measurement of payment term). Thus, there was a gap of only two days. Between the fourth quarter of 2000 and the fourth quarter of 2005, the gap fluctuated between negative 1.5 days (meaning the average payment term was greater than the average lead time) and 4.2 days. Starting in the first quarter of 2006, for yet-unknown reasons, the average lead time increased while the average payment term remained relatively flat. The average lead time reached a peak of 71.7 days

[2] This data comes from the U.S. Census Bureau's *Quarterly Financial Report for Manufacturing, Mining, Trade, and Selected Service Industries* and *Monthly Full Report on Manufacturers' Shipments, Inventories, and Orders.*

in the first quarter of 2009, yet the average payment term was only 44.3 days. This represents a gap of 27.4 days, the highest yet to be recorded. The average lead time fell back down to 49.9 days in the second quarter of 2011 while the average payment term was 36.8 days, thus the gap shrunk to 13.1 days. The average lead time began increasing after 2011. In the first quarter of 2015, the gap reached 27.3 days, which is only 0.1 days less than the high point reached in 2009. The average lead time continued to increase until hitting 69.8 days in the first quarter of 2016, although the average lead time had increased to 42.8 days, so the gap was only 27 days.

The peak in 2009 might be explained by the recession in the United States that the National Bureau of Economic Research (NBER) determined began in December 2007 and ended in June 2009. The NBER defines a recession as "a period of falling economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales."[3] A recession as identified by the NBER does not explain the gap between the average lead time and the average payment term seen in 2015 and 2016. (Going back to 1980, all peaks and troughs have been announced within two years of their "turning point date." By the time this thesis is published, more than four years have passed since the first quarter of 2016, yet the NBER has not identified a recession starting in those years.) However, the *New York Times* in late-2018 reported on a "mini-recession" occurring mostly in the U.S. industrial sector:

> "There was a sharp slowdown in business investment, caused by an interrelated weakening in emerging markets, a drop in the price of oil and other commodities, and a run-up in the value of the dollar.

[3] Business Cycle Dating Committee. Announcement Memos for the peak in December, 2007 (announced December 1, 2008) and the trough in June, 2009 (announced September 20, 2010). National Bureau of Economic Research.

> "The pain was confined mostly to the energy and agricultural sectors and to the portions of the manufacturing economy that supply them with equipment. Overall economic growth slowed but remained in positive territory. The national unemployment rate kept falling. Anyone who didn't work in energy, agriculture or manufacturing could be forgiven for not noticing it at all."[4]

If a "mini-recession" in 2016 caused the gap between the average lead time and the average payment term to spike in 2015, then two questions emerge. Why did a spike not occur during the recession between March 2001 and November 2001, as determined by the NBER?[5] If recessions cause the average lead time to be significantly longer than the average payment term, should not periods of economic expansion cause the average lead time to be significantly shorter than the average payment term, or at least return to parity? This thesis will not attempt to answer these questions, but practitioners should take away the following insights: (1) There was a point in recent history when the average lead time (as represented by backlog turnover days) and the average payment term were at parity. (2) Given that a gap currently exists, a specific firm can act to either favorably widen or close the gap for its own operations.

This thesis is designed to be read either in parts or in its entirety. First, the reader will be introduced to the existing literature on payment term and lead time determination in Chapter 2. Chapter 3 is primarily targeted towards supply chain practitioners. It contains formulas for determining payment terms that offset the impact of lead times on inventory. The same methodology can be used to determine payment terms that offset the impact of order quantity (Chapter 3.2) and ordering costs (Chapter 3.3) in the total cost equation, but the focus of this thesis

[4] Irwin, Neil. "The Invisible Recession of 2016." *New York Times*. September 30, 2018.
[5] Business Cycle Dating Committee. Announcement Memos for the peak in March, 2001 (announced November 26, 2001) and the trough in November, 2001 (announced July 17, 2003). National Bureau of Economic Research.

is on lead times. Chapters 4 and 5 are primarily targeted towards corporate finance practitioners. Those two sections introduce empirical research on payment terms and lead times. Companies with higher lead times (as represented by backlog days of sales) tended to extend longer payment terms to customers (as represented by DSO), and *vice versa*. Although this result indicates there is a relationship between lead times and payment terms, this thesis presents an observation of the fact, not an explanation for the type of relationship.

2. Literature Review

This thesis proposes linking payment terms to lead times to obtain better (shorter) lead times and a quantifiable understanding of vendor liquidity/cost preferences. This literature review will cover three broad sections to be built upon: How lead times are determined, how payment terms are determined, and why lead times increase. Because there do not appear to be any studies linking lead time and payment term determination, this thesis will narrow the gap.

2.1. How Lead Times are Determined

Lead times closely follow Little's Law: L = λ*W, where L is the "average number of items in the queuing system," λ is the "average number of items arriving per unit of time," and W is the "average waiting time in the system for an item." (Chhajed & Lowe, 2008) Alternatively, L is order backlog, λ is throughput per day, and W is lead time. Lead time can be determined by thus re-arranging the equation W = L ÷ λ:

$$Lead\ Time = \frac{Order\ Backlog}{Throughput\ per\ day}$$

Silver, Pyke, & Peterson (1998) define lead time as "the time that elapses from the moment at which it is decided to place an order, until it is physically on the shelf ready to satisfy customer demands." (p.48) They specify five unique categories of lead time: 1. Administrative time at stocking point; 2. Order transit time; 3. Time at the supplier; 4. Fulfillment transit time; and 5. Receipt and restocking. The third point, time at the supplier, will be the focus of this thesis and is most applicable to Little's Law.

Mir-Artigues and González-Calvet (2007) summarized three types of deploying productive activity, all related to time. First, sequential production involves "performing an elementary process after the other," such as is found in craftwork. Second, parallel production "involves a large number of elementary processes, all carried out simultaneously," such as growing multiple trees on the same farm. Third, line production or mass production consists of beginning the process of production of the next unit before the previous unit is entirely complete. The authors summarized sub-types of line manufacturing as jumbled production flow, disconnected flow (batch production), connected flow (assembly line production), and continuous flow. These sub-types range from maximum to null intermittency of the production flow and variety of output. Although helpful for categorization, the authors' framework does not seem to develop or incorporate a way to quantify the optimal amount of time spent on each type or sub-type, or how much backlog is suitable for each.

Hay (1970) attempted to identify an optimal backlog level and observed: "there is some positive level of unfilled orders which balances the cost savings attributable to an order backlog and the penalties associated with too large a backlog so that the net saving is maximized." (p. 532) Although this concept is not ground-breaking, it at least attempted to set an upper-bound on lead time.

The four sources listed above deal primarily with observing and accurately recording lead times for an operation but still do not help understand how the optimal lead time should be determined. Ohno (1988) contributed to the development of the Toyota Production System. He identified eight wastes: Overproduction, waiting, transportation, processing, inventory, movement, defects, and underutilized workers. Many of these wastes involve taking more time to do something than is required to add value for the customer. Thus, this was the first step in attempting to quantify the optimal lead time. Suri (1998) developed the philosophy known as Quick Response Manufacturing. It sets lead time reduction as a company-wide goal.

Of the literature related to lead time reviewed here, most provided helpful categorizations of lead time types or production activities that contribute to lead time. None of them provided a useful way to determine optimal lead time, although the Toyota Production System and Quick Response Manufacturing philosophies generally desire a shorter lead time compared to the alternative. Still, those philosophies are mostly focused on internal operations where payment terms are not a consideration.

2.2. How Payment Terms are Determined

Ng, Kiholm Smith, and Smith (1999) studied the determinants of payment terms (trade credit). They found payment terms to vary between industries but found minor variation within industries. This implies payment terms are determined by industry standards instead of specific relationships between buyers and sellers.

Trade credit is considered to be a way for large firms with better access to capital markets to finance sales to customers, but Klapper, Laeven, and Rajan (2012) found "many suppliers who extend credit that are much smaller and less well rated than their buyers, and are unlikely to have access to cheaper financing." (p. 841) The authors' empirical analysis of actual payment terms in almost 30,000 contracts found that larger buyers receive longer payment terms, European buyers have longer payment terms than North American buyers, and non-investment grade buyers had shorter payment terms than investment grade buyers, whereas smaller suppliers provided longer payment terms than larger suppliers and investment grade suppliers provided longer payment terms than non-investment grade suppliers. This research did not cover the aspect of lead time.

From a corporate strategy perspective, firms might extend payment terms for two reasons. Porter (1980) identified three generic strategies companies follow: Cost leadership, differentiation, and focus. Differentiation involves “creating something that is perceived *industrywide* as being unique.” (p. 37, emphasis in original) The first reason a firm might offer extended payment terms to customers is to differentiate itself from competitors who offer industry-standard payment terms. Porter (1980) also identified six barriers to entry, of which one was switching costs. He defined switching costs as “one-time costs facing the buyer of switching from one supplier’s product to another’s.” To overcome high switching costs, “new entrants must offer a major improvement in cost or performance in order for the buyer to switch from an incumbent.” (p. 10) The second reason a firm might offer extended payment terms to customers is to increase the switching costs (related to working capital) for its customer to switch to another vendor.

The two studies covering a large quantity of firms in different decades provide useful information to prove that payment terms are not directly related to inter-firm financing but did not draw a relationship to lead time. These works build a foundation for this thesis by helping prove payment terms are not directly driven by firm financing needs. Corporate strategy as explained by Michael Porter helps explain why payment terms might be higher for some customer-supplier relationships but does not explain the relationship between payment terms and lead times. There is still a gap related to payment terms and lead times for this thesis to narrow.

2.3. Why Lead Times Increase

In the section on determining lead time, Hay (1970) showed there was an optimal order backlog level that kept production running smoothly while also not making the customer wait too long. The lead proponents of the Toyota Production System and Quick Response Manufacturing created frameworks that favored reduced lead times over the alternative. Despite the prevalence of these two philosophies, there seems to be a tendency for lead times to increase over time instead of consistently decline.

Wight (1981) explained the increased lead time paradox: “As vendor backlogs picked up, vendors quoted longer lead times. Customers, in turn, ordered more to cover themselves out over the longer lead time, thus increasing the backlogs—causing another increase in lead times.” Silver, Pyke, and Peterson (1998) curiously found that lead times tend to increase during both periods of low sales and high sales. As sales decline, vendors are observed batching production to gain efficiency. As sales increase, backlog increases while throughput remains the same. Either longer lead times are a self-fulfilling prophecy, or lead times are destined to increase.

Ansari and Modarress (1990) advocated “just-in-time (JIT) purchasing.” They determined that lower lead times were the most important benefit of successful implementation of JIT purchasing. The authors admitted that successful implementation of JIT purchasing was limited and noted that suppliers were hesitant to commit to the program “until they are assured greater benefits than are normally received in the traditional buyer-supplier relationship.” Suppliers might recognize the positive aspects of JIT purchasing but also realize most of the benefit accrued to the buyer.

These studies provide a useful foundation for this thesis to build upon. They confirm the general tendency for lead times to increase, or at least confirm the difficulty in sustained lead time reduction. They also show there is a disconnect in how the benefits of lead time reduction are shared between buyers and suppliers.

2.4. Gaps in the Literature

This review of literature covered how lead times are determined, how payment terms are determined, and why lead times increase to provides foundation for this thesis, but also expose the gap. Lead time determination should be a relatively simple mathematical formula and in theory each firm has an optimal level of order backlog. Payment term determination has long been considered a financial instrument, but empirical studies show that there can be a non-financial determinant of payment terms. Although lead time determination should be simple, literature related to the difficulty of lead time reduction found suppliers tend to behave in a way that increases lead time even in counter-intuitive scenarios. Interestingly, the vast majority of literature that mentioned lead time assumed it was zero or—at most—one day for ease of calculation. That literature was not included for review in this thesis. Because the effect of lead time should be mathematically quantifiable, a way of splitting the benefits of lead time reduction between buyers and suppliers should be relatively straight forward. That is the gap this thesis will address.

3. Payment Term Offset Framework

This thesis proposes linking payment terms to lead times to obtain better (shorter) lead times and a quantifiable understanding of vendor liquidity/cost preferences. This chapter is targeted towards supply chain practitioners, whose day-to-day activities involve supplier negotiation and inventory planning. One framework is provided to understand tactically how working capital can be protected from supplier lead time proposals (Chapter 3.1). That framework can be extended to cover order quantity (Chapter 3.2) and ordering costs (Chapter 3.4), although the focus of this thesis is offsetting lead times with payment terms.

3.1 Pipeline and Safety Stock Inventory Offset Framework

The question this thesis seeks to answer is: Can payment terms be used to offset lead times? The foundation of the framework used in this thesis is the total cost equation, as shown in Equation 1. In a supply chain context, total cost includes purchase costs (the unit price multiplied by annual demand), ordering costs (the transaction cost multiplied by the number of transactions), and the holding cost. The holding cost consists of three parts: Cycle stock, safety stock, and pipeline inventory. For simplicity, the order quantity is determined by the economic order quantity formula, as shown in Equation 2, but the framework is not totally dependent on this assumption.

Total Cost Equation = $cD + \ c_t\left(\frac{D}{Q}\right) + c_e(\frac{Q}{2} + k\sigma_{DL} + \frac{D}{Y}L)$ (Eq. 1)

Economic Order Quantity (EOQ) = $\sqrt{(2Dc_t)/c_e}$ (Eq. 2)

Where:

- c: product cost
- c_e: holding cost
- c_t: ordering cost
- Q: order quantity (as determined by EOQ)
- D: annual demand

- Y: days per year
- k: safety factor (inverse of the standard normal cumulative distribution function)
- σ_{DL}: standard deviation of demand over lead time
- L: lead time

Assumption #1: All inputs are greater than zero.

In Equation 1, the lead time variable does not differentiate between production lead time and transit lead time. The safety factor needs to be applied to the entire lead time, whereas pipeline inventory only includes inventory in transit. To accommodate for this, the equation is altered:

$$\text{TC} = cD + c_t\left(\frac{D}{Q}\right) + c_e\left(\frac{Q}{2} + k\sigma_w + \frac{D}{Y}L_t\right) \qquad \text{(Eq. 3)}$$

Where:
- L_w: $L_t + L_p$
- L_t: transit lead time
- L_p: production lead time
- σ_w: standard deviation of demand over L_w (production and transit)

Assumption #2: The whole lead time (L_w) is less than the number of days per year (Y), otherwise c_e and c_t become inaccurate.

In Equation 3, the holding cost is applied to a safety stock level that accounts for the entire lead time, as well as the in-transit inventory. Whereas Equation 1 double counted production lead time as pipeline inventory, Equation 3 does not.

The defect of Equation 3 is it does not account for payment terms. Although a firm might take ownership of product as it becomes in-transit, the firm likely pays for the product a few weeks later. Payment terms should offset the cost of holding product. To accommodate this, Equation 3 is altered:

$$\text{TC} = cD + c_t\left(\frac{D}{Q}\right) + c_e\left(\frac{Q}{2} + k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P\right) \qquad \text{(Eq. 4)}$$

Where:

- P: Payment term (Note: P should be scaled with Y, so if $Y = 250$, then Net 30, Net 60, and Net 90 in a 365-day year scale to approximately 21 days, 41 days, and 62 days, respectively, in a 250-day year.)

Note that Equation 3 and Equation 4 obtain the same result when $P = 0$. The implicit assumption of the total cost equation (both Equation 1 as the standard form and Equation 3 as the updated form) is payment is settled immediately. The advantage of accounting for payment terms in the total cost equation (as done in Equation 4) is both added realism and flexibility. The variable P can be a positive or negative number. A positive P implies payment occurs after ownership transfers from the buyer to the seller (such as Net 30 or Net 60). A negative P implies payment occurs before ownership transfers from the seller to the buyer (such as pre-payment).

The purpose of this thesis is to understand the relationship between L_w and P, and how they can offset each other. The goal is to find P such that the impact of L_w on the buyer is offset (zero). To do this, Equation 4 can be converted into the total relevant cost equation for lead time and payment terms.

$$\text{TRC} = c_e\left(k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P\right) \qquad \text{(Eq. 5)}$$

The difference between Equation 4 (the total cost equation) and Equation 5 (the total relevant cost) is purchase cost (c*D), ordering cost (c_t*[D/Q]), and cycle stock ($Q/2$) were dropped because they are not impacted by lead time or payment term. To understand how P offsets inventory determined by lead time, TRC can be set to zero.

$$0 = c_e\left(k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P\right) \qquad \text{[divide both sides by } c_e\text{]}$$

$$0 = k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P \qquad \text{[move } P \text{ to the left-hand side]}$$

$$\frac{D}{Y}P = k\sigma_w + \frac{D}{Y}L_t \qquad \text{[multiply both sides by } \tfrac{Y}{D} \text{ to isolate } P\text{]}$$

$$P = \frac{Yk\sigma_w}{D} + L_t \qquad \text{(Eq. 6)}$$

Equation 6 provides a very simple way to calculate *P* such that the effect of lead time on inventory is offset by payment terms. Examining the equation provides insights:

1. If a seller believes the marginal benefit of producing over a longer period outweighs the marginal cost of capital, then the seller still gains by extending payment terms to the level calculated in Equation 6 at no additional downside to the buyer.
2. Under the best-case scenario when $\sigma_w = 0$, meaning there is zero variability of demand over the whole lead time, then $P = L_t$.
3. Similarly, when $k = 0$, meaning the cycle service level is 50%, then $P = L_t$.
4. However, given Assumption #1, $\sigma_w > 0$ and $k > 0$, so there is variability of demand over the whole lead time and cycle service level is higher than 50%. Therefore, $P > L_t$.

Equation 6 is useful for the buyer when L_w is known, meaning the seller's production lead time (L_p) can be calculated using Little's Law and transit lead time (L_t) is generally known. Buyers commonly have corporate finance guidelines for payment terms, but rarely have corporate guidance on acceptable lead times. How should the seller determine production lead times such that a buyer-imposed payment term do not cause the seller to subsidize the buyer's inventory? The variable L_p can be revealed in Equation 6 by re-working σ_w into its original components, as shown in Equation 7.

$$\sigma_w = \frac{\sigma}{\sqrt{Y \div (L_t + L_p)}} \qquad \text{(Eq. 7)}$$

After substituting Equation 7 into Equation 6 (with steps shown in Appendix A), L_p can be solved for as shown in Equation 8.

$$L_p = \frac{Y}{\left(\frac{Yk\sigma}{DP-DL_t}\right)^2} - L_t \qquad \text{(Eq. 8)}$$

Equation 8 reveals further insights that were not directly obvious while calculating the payment term that offsets the effect of the seller's lead time on the buyer's inventory in Equation 6:

1. Assumption #1 limited all variables to positive numbers. If Y, k, or σ were zero, there would be a zero in a denominator, thus leaving L_p undefined.
2. The insights from Equation 6 show $P > L_t$. This is helpful to maintain for Equation 8, because if $P = L_t$, then again there is a zero in a denominator, thus leaving L_p undefined. Additionally, the squared operation converts a negative number into a positive number, so earlier pre-payment (a negative P) trends towards a longer production time. Because transit time will never be negative, then $P > L_t$ also restricts P to positive numbers.
3. As $D*P$ in relation to $D * L_t$ gets smaller, the value of L_p approaches negative L_t. Because production time cannot be negative (or zero), the implication is there must be some distance between P and L_t.
4. Assumption #2 had the restriction $L_w < Y$. As $D*P$ in relation to $D * L_t$ gets larger, L_p increases rapidly. In fact, depending on which numbers are used for the other variables, L_p far exceeds Y before P reaches the equivalent of Net 90.

The payment term offset framework (as shown in Equation 6) is useful because it is neutral. The framework's neutrality comes from its reliance on time (days) as a unit of measure, instead of costs. Imagine a scenario where a buyer attempts to offset the impact of long lead times (higher holding costs) by negotiating a reduced purchase price. The inputs that convert the total cost equation into currency units are c (purchase price), c_t (ordering cost), and c_e (holding cost). The purchase price is observable to both the buyer and the seller, but the buyer's ordering cost and holding cost are not observable to the seller. The buyer rarely—if ever—knows the true ordering and holding costs. Even if the buyer knows the true ordering and holding costs, the buyer has an incentive to report inflated numbers to the seller. By using a different measurement, the payment term offset framework avoids this issue.

The variables needed to determine the payment term in Equation 6 are Y (days per year), k (safety factor), σ_w (variation of demand over the whole lead time), D (annual demand), and L_t (transit lead time). Days per year is observable to both the buyer and the seller. The safety factor is a statistics property that is observable to both the buyer and the seller. If demand and the variation of demand over the whole lead time are based off historical data, then both are observable to the buyer and the seller. Similarly, transit lead time is observable. A summary of variables and whether or not they are observable is shown in Table 1.

Table 1. Total Cost Equation Variables		
Variable	**Observable to Seller?**	**Observable to Buyer?**
Y (days per year)	Yes	Yes
k (safety factor)	Yes	Yes
σ_w (variation over lead time)	Yes	Yes
D (annual demand)	Yes	Yes
L_t (transit lead time)	Yes	Yes
c_e (holding cost)	No	Maybe
c_t (ordering cost)	No	Maybe

3.2 On Hand Inventory Offset Framework

The purpose of this thesis is to understand the relationship between L_w and P, and how they can offset each other. It might benefit the reader to briefly show how the principle developed in Equation 6 can be applied to on hand inventory as a whole and not just the portion impacted by lead time. Although the buyer can offset the impact of longer lead times using the lead time offset framework (Equation 6), the buyer has a similar issue as before dealing with an increased order quantity mandated by the seller. Cycle stock is calculated as half the order quantity, so a larger order quantity causes higher cycle stock levels. This negatively impacts the buyer's holding costs, but the seller might gain from producing fewer large batches instead of more small batches. The order quantity dynamic is like the lead time dynamic in that—to a certain point—the seller benefits from a longer lead time and larger order size while the buyer suffers.

In Equation 5, cycle stock was removed from the total cost equation because it is not related to lead time. It can be added back to understand the total relevant cost for the buyer of the lead time and order quantity given by the seller.

$$\text{TRC} = c_e\left(\frac{Q}{2} + k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P\right) \quad \text{(Eq. 9)}$$

$$P = \frac{YQ}{2D} + \frac{Yk\sigma_w}{D} + L_t \quad \text{(Eq. 10)}$$

The steps for converting Equation 9 into Equation 10 can be found in Appendix B. Equation 10 provides a very simple way to calculate P such that the effect of lead time and order quantity on inventory is offset by payment terms. Examining the equation provide similar insights as for Equation 6:

1. If a seller believes the marginal benefit of producing over a longer period and in larger batches outweighs the marginal cost of capital, then the seller still gains by extending payment terms to the level calculated in Equation 10 at no additional downside to the buyer.
2. As σ_w approaches 0, meaning demand is less variable, and as Q approaches 1, meaning the seller has eliminated batched production, P approaches L_t. It still holds that $P > L_t$.

3.3 On Hand Inventory and Ordering Cost Offset Framework

The first framework introduced in this thesis focused on offsetting inventory determined by lead times, which is safety stock ($k\sigma_w$) and pipeline inventory ($([D/Y] * L_t)$. The on hand inventory offset framework in the previous chapter incorporates cycle stock (Q/2) by converting units into time. The remaining components of the total cost equation used in this thesis are purchase costs (c*D) and ordering costs (c_t*[D/Q]). Ordering costs in theory vary with the size of Q. Lead times are also at least somewhat affected by Q, assuming it takes longer to produce a larger quantity than a smaller quantity. In Table 1, we see that c_t is not observable to the seller and only might be observable to the buyer. However, the economic order quantity model allows for a way to relate ordering costs to cycle stock holding costs. The economic order quantity model determines the point where ordering costs are equal to cycle stock costs. Equation 2 is reproduced below and re-worked backwards to show that ordering costs are set equal to cycle stock holding costs at economic order quantity conditions.

$Q = \sqrt{2Dc_t \div c_e}$ [square both sides]

$Q^2 = \frac{2Dc_t}{c_e}$ [multiply both sides by $\frac{c_e}{2}$]

$\frac{c_eQ^2}{2} = Dc_t$ [divide both sides by Q]

$c_e(\frac{Q}{2}) = c_t(\frac{D}{Q})$ (Eq. 11)

Given this insight, Equation 4 can be modified as shown below.

TC = $cD + c_t\left(\frac{D}{Q}\right) + c_e(\frac{Q}{2} + k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P)$ (Eq. 4)

TC = $cD + c_t\left(\frac{D}{Q}\right) + c_e(\frac{Q}{2}) + c_e(k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P)$ [isolate holding costs]

TC = $cD + c_e(\frac{Q}{2}) + c_e(\frac{Q}{2}) + c_e(k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P)$ [incorporate Eq. 11]

TC = $cD + c_e(Q) + c_e(k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P)$ [combine like terms]

TC = $cD + c_e(Q + k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P)$ (Eq. 12)

Now that Equation 4 has been updated as Equation 12, Equation 5 can also be updated to include ordering costs as Equation 13.

TRC = $c_e(Q + k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P)$ (Eq. 13)

The difference between Equation 12 and Equation 13 is the purchase cost (*c*D*) has been removed because it is not relevant to lead time. To understand how *P* can offset ordering costs at economic order quantity conditions, cycle stock, and inventory determined by lead time, TRC can be set to zero.

$0 = c_e(Q + k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P)$ [divide both sides by c_e]

$0 = Q + k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P$ [move *P* to the left-hand side]

$\frac{D}{Y}P = Q + k\sigma_w + \frac{D}{Y}L_t$ [multiply both sides by $\frac{Y}{D}$ to isolate *P*]

$P = \frac{Y(Q+k\sigma_w)}{D} + L_t$ (Eq. 14)

Equation 14 provides a very simple way to calculate *P* such that the effect of lead time and order quantity on inventory and the effect of order quantity on ordering costs are offset by payment terms. Examining the equation provides similar insights as for Equation 6 and 10:

1. If a seller believes the marginal benefit of producing over a longer period and/or in larger batches outweighs the marginal cost of capital, then the seller still gains by extending payment terms to the level calculated in Equation 14 at no additional downside to the buyer.

2. As σ_w approaches 0, meaning demand variability is declining, and as Q approaches 1, meaning the seller has eliminated batched production, P approaches L_t. It still holds that $P > L_t$.

3.4 Offset Framework Summary

The frameworks developed in this thesis segment payment term offsets into three categories: Pipeline and Safety Stock Inventory, On Hand Inventory, and On Hand Inventory and Ordering Cost. The Pipeline Safety Stock Inventory Offset Framework is suitable for buyer-seller relationships where the buyer can offset inventory impacted by the seller's lead time. The On Hand Inventory Offset Framework applies to buyer-seller relationships where the buyer can offset cycle stock—which is impacted by the seller's order quantities—and inventory impacted by the seller's lead time. The On Hand Inventory Ordering Cost Offset Framework expands on the previous framework, but is only applicable when the economic order quantity is used. Developing each framework provided insights into how payment terms relate to lead times.

All three frameworks established transit time as the lower-bound for payment terms. Payment terms should be longer than transit lead times, even with low demand variability and no minimum order quantities. These frameworks were focused on calculating a payment term given a lead time, but the production lead time can be back calculated with a given payment term. Although most of this thesis can be considered to have been written from the buyer's perspective, the neutrality of the framework gives it value. Sellers can use the framework to determine a payment term that does not subsidize the buyer's working capital, or at least quantify the size of the subsidy. Not only did this also confirm that the payment term should be longer than the transit lead time, it also showed why there should be considerable distance between the payment term and the transit lead time. Even though all three frameworks established transit time as the lower bound, the back calculation showed that the upper limit was far short of Net 90. Now that these frameworks have been developed, the next chapters will explore the relationship between payment terms and lead times on publicly listed companies' financial statements.

4. Research Methodology

This thesis provides a framework for determining payment terms such that the impact of lead times on the buyer are offset. Chapter 3 was targeted towards supply chain practitioners. The current chapter and Chapter 5 will compare lead times and payment terms for a sample of publicly listed companies and is directed towards corporate finance practitioners.

The source of information is the United States Securities and Exchange Commission's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. As of this writing, the SEC's website allows users to search for specific keywords in all EDGAR filings over the prior four years.

Search parameters:

- Search for Text: "backlog"
- In Form Type: 10-K (annual report)
- Standard Industry Classification: 3310 Steel Works, Blast Furnaces & Rolling & Finishing Mills; 3312 Steel Works, Blast Furnaces & Rolling Mills; 3317 Steel Pipe & Tubes; 3350 Rolling Drawing & Extruding of Nonferrous Metals; 3360 Nonferrous Foundries (Castings); 3390 Miscellaneous Primary Metal Products; 3411 Metal Cans; 3412 Metal Shipping Barrels, Drums, Kegs & Pails; 3420 Cutlery, Handtools & General Hardware; 3440 Fabricated Structural Metal Products; 3442 Metal Doors, Sash, Frames, Moldings & Trim; 3460 Metal Forgings & Stampings; 3490 Miscellaneous Fabricated Metal Products
- Start Date: January 1, 2019
- End Date: December 31, 2019

A total of 28 companies were selected for the data set. The list of companies used can be found in Appendix C. For a company to be included in the data set, it had to disclose the following information:

1. Annual sales (statutorily required);
2. Annual cost of goods sold (statutorily required);
3. Statements about backlog (optional);
4. Trade receivables (statutorily required, although companies with high levels of service businesses that did not differentiate between product-related trade receivables and service-related trade receivables were excluded);
5. Statements about receivable factoring (optional);
6. Inventory values for finished goods, work-in-process, and raw materials (optional);
7. Interest expense (optional);
8. Total debt (statutorily required).

From that information, the following was calculated:

1. Gross margin (annual sales minus annual cost of goods sold divided by annual sales);
2. Backlog days of sales (disclosed backlog order value divided by annual sales and multiplied by 365), if available;
3. Finished goods as a percent of inventory (finished goods inventory value divided by total inventory value);
4. Days of sales outstanding (trade receivables divided by annual sales and multiplied by 365);
5. Raw and In-Process Ratio (raw materials and work-in-process divided by annual cost of goods sold and multiplied by 365);

6. Average interest rate (interest expense divided by total debt at year end).

The 28 companies in the data set generated $96.6 billion of sales in the fiscal year disclosed in 2019 at a cost of $73.1 billion, representing a weighted average gross margin of 24.3%. The smallest company in the data set by sales revenue generated $228.0 million and the largest generated $14.3 billion. The lowest gross margin was 8.6% and the highest was 50.0%. Of the 28 companies in the data set, 16 provided backlog order value. For these 16 companies, backlog order value totaled $11.9 billion. The weighted average backlog days of sales for these 16 companies was 90.7 days. Backlog days of sales ranged from a low of 10.6 days to a high of 285.2 days. The other 12 companies made statements that their backlog order value was not material to their business. Five of those 12 indicated backlog was not significant because lead times to their customers were short. Trade receivables totaled $13.5 billion. This number is between $1.5 billion and $2.0 billion lower than otherwise because six of the 28 companies disclosed they sold accounts receivables to third parties (also known as "factoring"). The weighted average days of sales was 51.0 days and the range was between 39.8 days and 93.3 days. Finished goods were valued at $6.5 billion, work-in-process was valued at $4.2 billion, and raw materials were valued at $4.4 billion, implying a finished good proportion of 42.9%. The finished good proportion range was 0.8% to 76.7%. The weighted average RIP ratio was 43.0 days. The range was between 18.2 days and 134.7 days. The median interest rate was 5.06%, with 50% of values falling between 6.20% and 4.36%. The minimum average interest rate was 1.79% and the maximum average interest rate was 12.36%, both of which appear to be caused by a sudden increase or decrease in year-end debt levels.

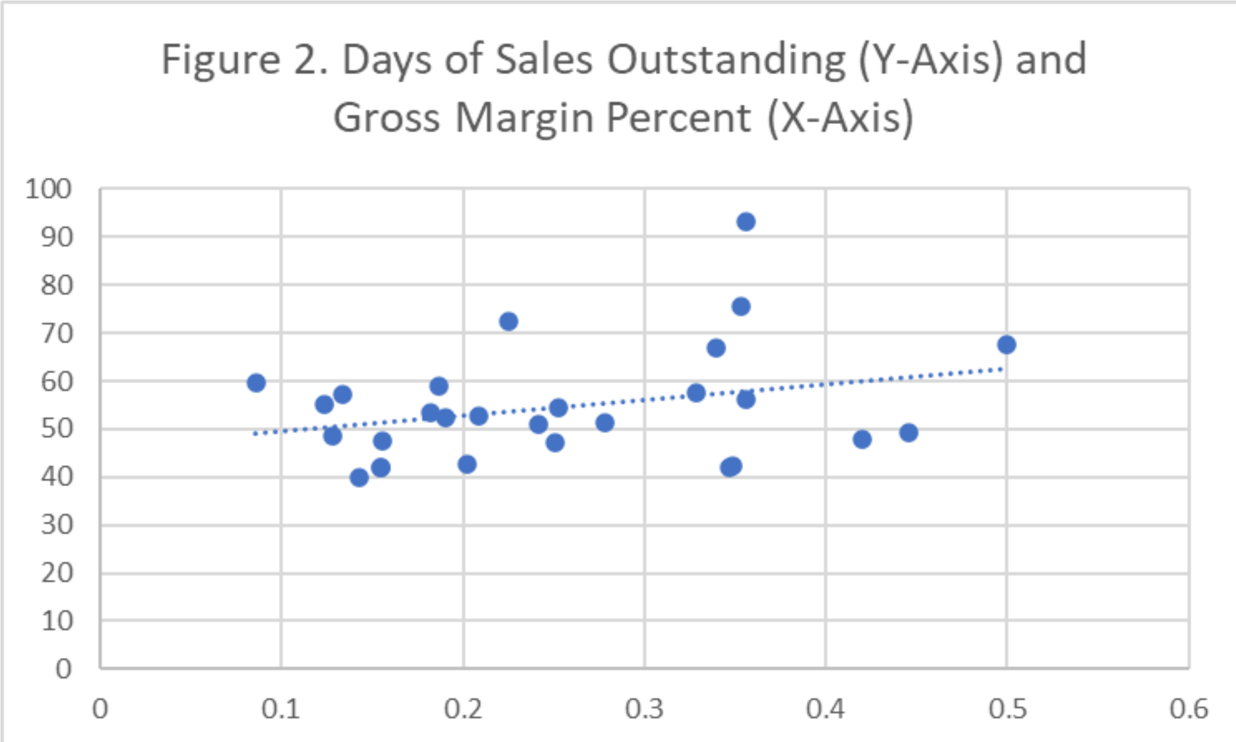
The research scope originally covered more Standard Industry Classification codes, but the final focus was on companies related to the industries listed in the search parameters due to availability of comparable data. Among the 15 companies analyzed in the food industry, none of them disclosed backlog order values. Only three provided work-in-process inventory numbers. Among the 14 companies analyzed in the chemicals industry, only five disclosed backlog order values. Companies related to rubber (3011 Tires & Inner Tubes; 3050 Gaskets, Packg & Sealg Devices & Rubber & Plastics Hose; and 3060 Fabricated Rubber Products, NEC) provided usable information, but there were only five companies in the grouping. There was a similar issue for plastic products and industrial equipment. Researchers with better access to data for a larger group of companies in other specific industries can replicate the findings of this thesis, but due to data constraints, this thesis focused on the 13 industry classifications listed in the search parameters.

5. Findings

This chapter shows the results for the five independent variables, in graphical form and table form. Although some of the graphs appear to have a sloping trend line—implying a relationship exists—the high p-values indicate they likely do not. The summary statistics are displayed below in Table 2. The adjusted R square and p-values are the focus of most of the next chapter. A higher adjusted R square is considered better than a lower adjusted R square. A lower p-value is considered better than a higher p-value. In these examples, the days of backlog performed the best because it had the highest adjusted R square and the lowest p-value. The finished goods proportion performed the worst because it had the lowest adjusted R square and the highest p-value. Specific results for each independent variable are shown on the following pages and further discussion of the results can be found in the next chapter.

Table 2. Summary Statistics

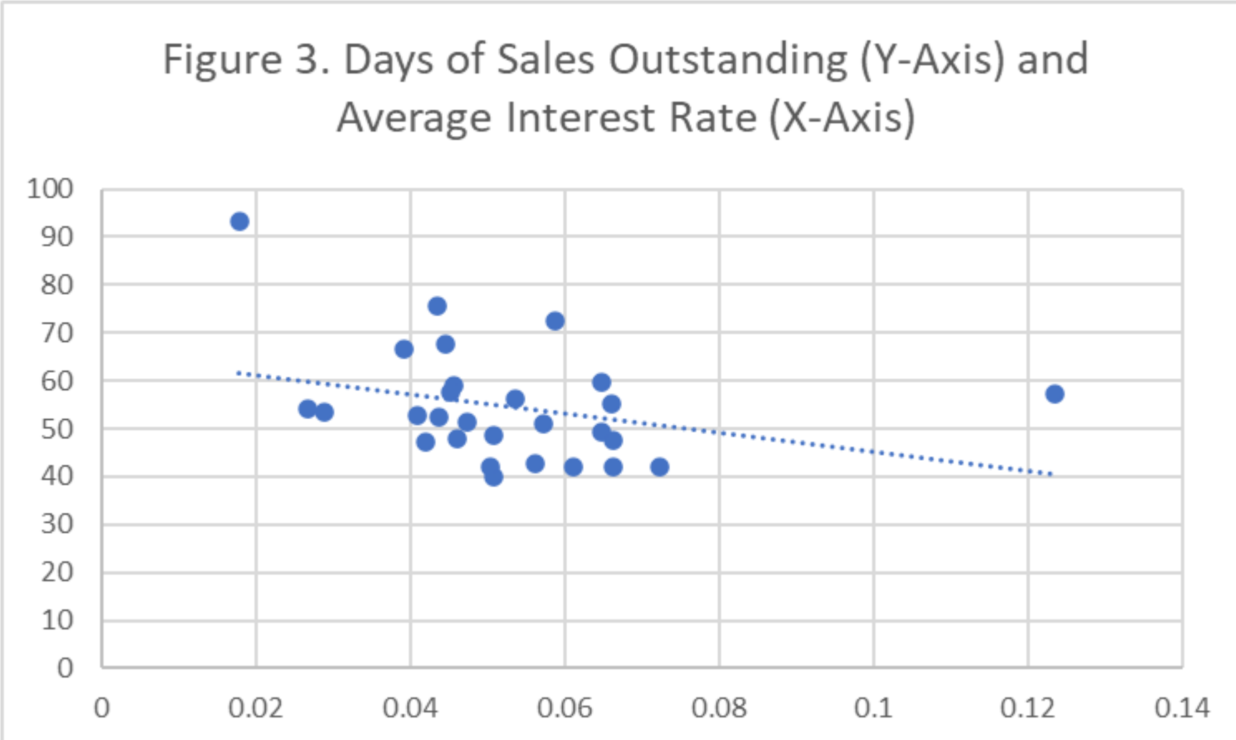
Independent Variable	Adjusted R Square	P-value
Gross Margin Percent	0.05567	0.12
Average Interest Rate	0.06553	0.10
Finished Goods Proportion	-0.03778	0.90
Raw-and-in-Process Ratio	-0.01081	0.41
Days of Backlog	0.34798	0.01



Regression Statistics	
Multiple R	0.30107
R Square	0.09064
Adjusted R Square	0.05567
Standard Error	11.64371
Observations	28

	df	***SS***	***MS***	***F***	***Significance F***
Regression	1	351.38	351.38	2.59	0.12
Residual	26	3524.98	135.58		
Total	27	3876.36			

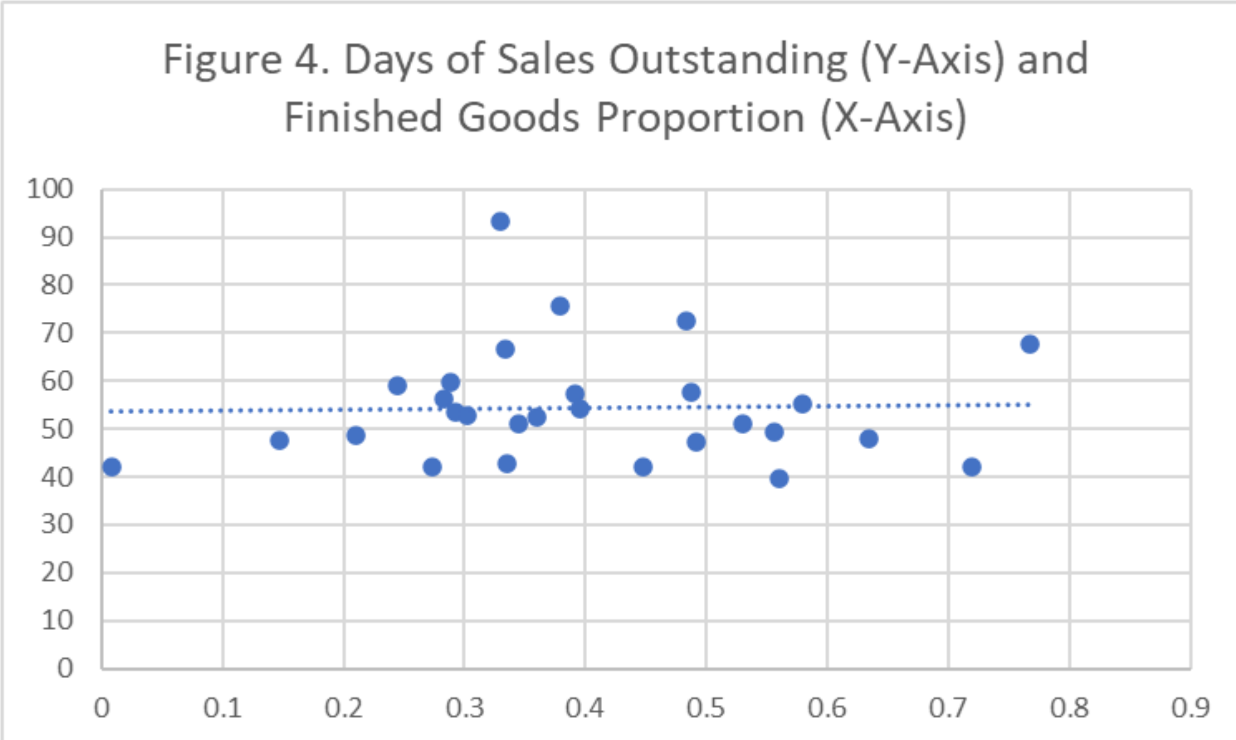
	Coefficients	***Standard Error***	***t Stat***	***P-value***	***Lower 95%***	***Upper 95%***	***Lower 95.0%***	***Upper 95.0%***
Intercept	46.19	5.64	8.19	<0.01	34.60	57.78	34.60	57.78
X Variable 1	33.00	20.50	1.61	0.12	-9.13	75.13	-9.13	75.13



Regression Statistics	
Multiple R	0.31645
R Square	0.10014
Adjusted R Square	0.06553
Standard Error	11.58274
Observations	28

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	388.20	388.20	2.89	0.10
Residual	26	3488.16	134.16		
Total	27	3876.36			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	65.08	6.57	9.91	<0.01	51.58	78.58	51.58	78.58
X Variable 1	-200.09	117.63	-1.70	0.10	-441.8	41.70	-441.8	41.70

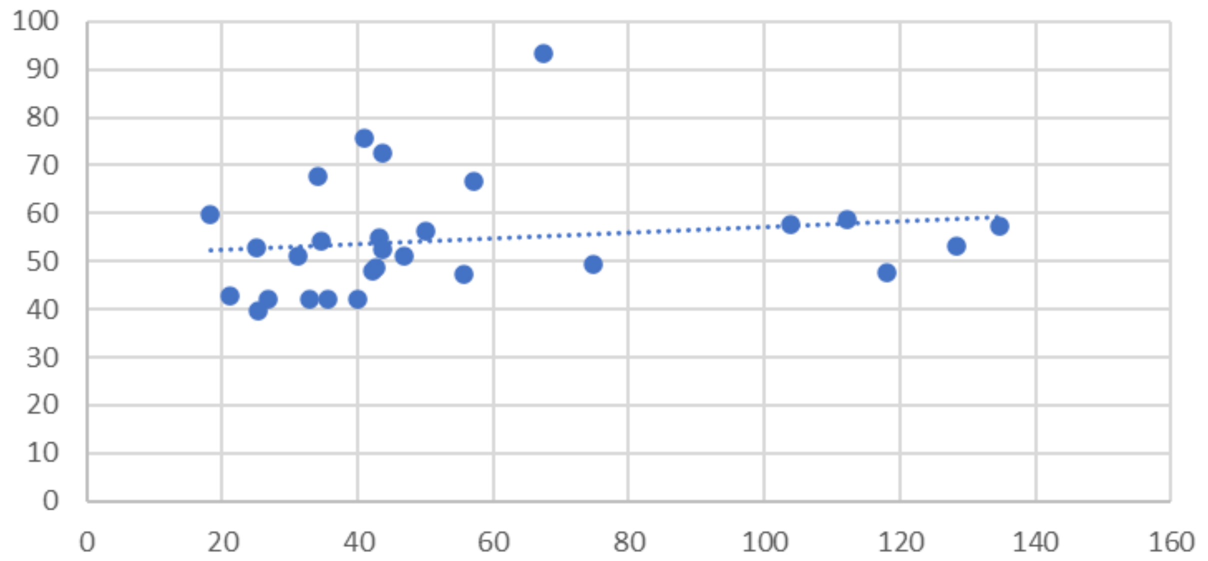


Regression Statistics	
Multiple R	0.0255
R Square	0.0006
Adjusted R Square	-0.0377
Standard Error	12.2063
Observations	28

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.52	2.52	0.02	0.90
Residual	26	3873.84	148.99		
Total	27	3876.36			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	53.83	5.99	8.98	<0.01	41.51	66.15	41.51	66.15
X Variable 1	1.80	13.86	0.13	0.90	-26.68	30.29	-26.68	30.29

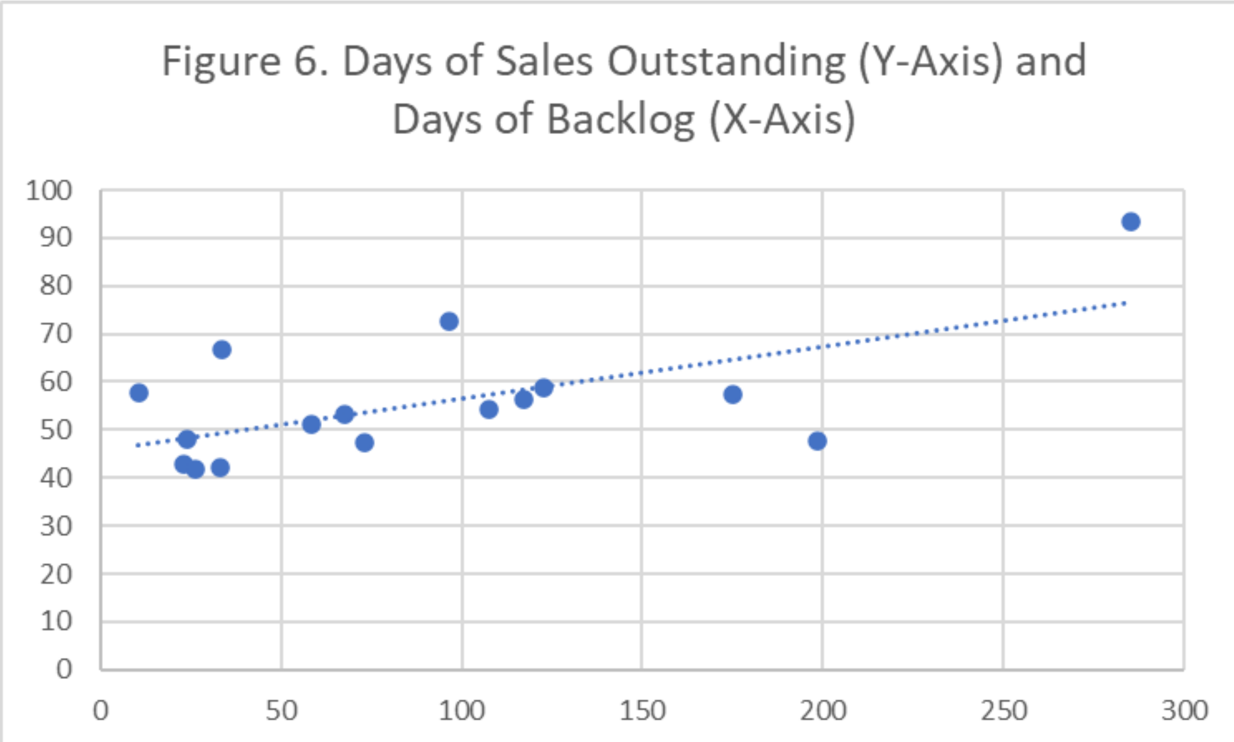
Figure 5. Days of Sales Outstanding (Y-Axis) and RIP Ratio (X-Axis)



Regression Statistics	
Multiple R	0.1631
R Square	0.0266
Adjusted R Square	-0.0108
Standard Error	12.0466
Observations	28

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	103.21	103.21	0.71	0.41
Residual	26	3773.15	145.12		
Total	27	3876.36			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	51.37	4.40	11.67	<0.01	42.32	60.42	42.32	60.42
X Variable 1	0.06	0.07	0.84	0.41	-0.08	0.20	-0.08	0.20



Regression Statistics	
Multiple R	0.62566
R Square	0.39145
Adjusted R Square	0.34798
Standard Error	10.62835
Observations	16

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1017.30	1017.30	9.01	0.01
Residual	14	1581.47	112.96		
Total	15	2598.77			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	45.85	4.22	10.87	<0.01	36.80	54.90	36.80	54.90
X Variable 1	0.11	0.04	3.00	0.01	0.03	0.19	0.03	0.19

6. Discussion

The findings align with the literature on payment terms and provide a basis for the framework introduced in this thesis. Five independent variables were tested against days of sales (DSO) as the dependent variable. Two were related to corporate finance considerations and three were related to lead times. Although there appears to be relationship between one of the lead time variables, this thesis only observes the relationship. It does not provide an explanation for the relationship.

From a corporate finance perspective, gross margin percent and average interest rates did not seem to have much of an impact on DSO. This result confirms the findings of Ng, Kiholm Smith, & Smith (1999) that financial considerations were not the main determinant of payment terms. Gross margin percent (Figure 2) explained only 5.6% of the variation in DSO. If we expect that a higher gross margin leads to longer customer payment terms, then the slope of the line should be positive. The p-value for our independent variable coefficient was 0.12, indicating the slope of the line might not be positive. Similarly, the average interest rate (Figure 3) explained only 6.5% of the variation in DSO. If we expect that a lower average interest rate leads to longer customer payment terms, then the slope of the line should be negative. The p-value for the average interest rate coefficient was 0.10, also indicating the slope of the line might not be negative. Although the trend lines on the graphs appear to be positively or negatively slopping, there is a statistical likelihood they are not.

Because companies do not publish lead times, and only a few companies disclosed backlog, two proxies were used for lead time. The first was finished goods as a percent of inventory (Figure 4). A company with a higher proportion of finished goods likely has faster fulfillment times for customers. The second was the raw-and-in-process (RIP) ratio (Figure 5). A company that converts raw materials and work-in-process into finished goods faster likely has shorter lead times than otherwise. The proportion of finished goods explained essentially 0% of the variation in payment terms. If a higher proportion of finished goods meant faster customer lead times (and therefore faster payment), then the slope of the line should be positive. The p-value is 0.90, indicating the slope is not positive. (The trend line in the graph appears to be flat.) The RIP ratio also explained essentially 0% of the variation in DSO. If we expect a longer RIP ratio to imply a longer customer lead time and lead to longer payment terms, then we would expect the slope to be positive. The p-value for the RIP ratio as an independent variable coefficient was 0.41. Those numbers are better than for the finished goods proportion, but far worse than the corporate finance independent variables.

The last variable is different from the previous four. All 28 companies in the sample reported the information required to calculate gross margin percent, average interest rate, finished good proportion, and RIP ratio. Only 16 companies disclosed a backlog value. Thus, days of backlog could only be used as an independent variable for these 16 companies. Days of backlog explained 34.8% of the variation in DSO (Figure 6). That is not a very high number, but it is much higher than the corporate finance independent variables that have long held sway over perceived determinants of payment terms. If we expect higher days of backlog to lead to longer customer payment terms, then the slope of the line should be positive. The p-value for days of backlog as an independent variable coefficient is 0.01. That means the slope is positive.

The results agreed with prior literature on payment terms that found profitability (as defined by gross margin) and borrowing cost (as defined by average interest rate) had minimal relation to DSO. The two measures of internal lead time—finished good proportion and RIP ratio—appear to have no relationship to DSO. For companies that reported backlog values, there does appear to be a relationship between days of order backlog and DSO. (Figure 2.) Even though days of backlog only explained 34.8% of the variance in DSO, this number is much larger than the amount explained by average interest rate and gross margin—two metrics that have long been considered the drivers of payment terms.

7. Conclusion

Can payment terms be used to offset lead times? Data from the manufacturing sector in the United States showed lead times and payment terms were once near parity, but the average lead time has increased while the average payment term has changed slightly. This thesis provided a framework to calculate a payment term that offsets inventory holding costs driven by lead time. The same principle can be used to offset order quantity and even ordering costs.

All three frameworks established transit time as the lower-bound for payment terms. Payment terms should be longer than transit lead times, even with low demand variability and no minimum order quantities. One real-world implication is that pre-payment is inappropriate. If the payment term must be greater than the transit time, and pre-payment implies a negative payment term, then transit time must also be negative. This is not possible. The other real-world implication is that international suppliers should have longer payment terms than domestic suppliers, given the fact that transit time is generally longer from international suppliers than from domestic suppliers.

These frameworks were focused on calculating a payment term given a lead time, but the production lead time can be back calculated with a given payment term. Although most of this thesis can be considered to have been written from the buyer's perspective, the neutrality of the framework gives it value. Sellers can use the framework to determine a payment term that does not subsidize the buyer's working capital, or at least quantify the size of the subsidy. Not only did this also confirm that the payment term should be longer than the transit lead time, it also showed why there should be considerable distance between the payment term and the transit lead time. Even though all three frameworks established transit time as the lower bound, the back calculation showed that the upper limit was far short of Net 90.

Empirical evidence shows that companies with higher lead times (as represented by backlog days of sales) tended to extend longer payment terms to customers (as represented by DSO), and vice versa. Although this result indicates there is a relationship between lead times and payment terms, this thesis presents an observation of the fact, not an explanation for the type of relationship.

The ideas developed in this thesis provide two opportunities. The first is implementation. The updated total cost equation found in Chapter 3 should be used by practitioners. Payment term determination should transfer from a corporate finance consideration to a supply chain tool. The optimal supplier lead time exists, so payment terms should be used the find it without coming at the expense of the buyer. The second opportunity is further research. This thesis examined aggregated financial statements. Many companies did not disclose the information required to perform that analysis done in Chapters 4 and 5. Analysts with access to proprietary information can examine their own customer and supply base. Do customers with longer lead times also have longer days of sales outstanding than customers with shorter lead times? Do suppliers with longer lead times have longer days of payables outstanding that suppliers with shorter lead times?

The question this thesis asked was: Can payment terms be used to offset lead times? The frameworks showed how to offset lead times with payment terms and the empirical research observed a relationship between them. The next question for future research to answer is: What type of relationship is it?

Appendix A

To find *P* when L_p is known:

$$P = \frac{Yk\sigma_w + DL_t}{D}$$

To find L_p when P is known:

$$P = \frac{Yk\sigma_w + DL_t}{D}$$

$$P = \frac{Yk\left(\frac{\sigma}{\sqrt{Y \div (L_t + L_p)}}\right) + DL_t}{D}$$

$$DP = \frac{Yk\sigma}{\sqrt{Y \div (L_t + L_p)}} + DL_t$$

$$\sqrt{Y \div \left(L_t + L_p\right)}(DP) = Yk\sigma + (DL_t)\sqrt{Y \div (L_t + L_p)}$$

$$Yk\sigma = (DP - DL_t)\sqrt{Y \div (L_t + L_p)}$$

$$\sqrt{Y \div (L_t + L_p)} = \frac{Yk\sigma}{DP - DL_t}$$

$$\frac{Y}{(L_t + L_p} = \left(\frac{Yk\sigma}{DP - DL_t}\right)^2$$

$$Y = (L_t + L_p)\left(\frac{Yk\sigma}{DP - DL_t}\right)^2$$

$$L_t + L_p = \frac{Y}{\left(\frac{Yk\sigma}{DP - DL_t}\right)^2}$$

$$L_p = \frac{Y}{\left(\frac{Yk\sigma}{DP - DL_t}\right)^2} - L_t$$

Appendix B

$0 = c_e(\frac{Q}{2} + k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P)$ [divide both sides by c_e]

$0 = \frac{Q}{2} + k\sigma_w + \frac{D}{Y}L_t - \frac{D}{Y}P$ [move *P* to the left-hand side]

$\frac{D}{Y}P = \frac{Q}{2} + k\sigma_w + \frac{D}{Y}L_t$ [multiply both sides by $\frac{Y}{D}$ to isolate *P*]

$P = \frac{YQ}{2D} + \frac{Yk\sigma_w}{D} + L_t$

Appendix C

Company Name
HAYNES INTERNATIONAL, INC.
WORTHINGTON INDUSTRIES, INC.
GIBRALTAR INDUSTRIES, INC.
CARPENTER TECHNOLOGY CORPORATION
TITAN INTERNATIONAL, INC.
SYNALLOY CORPORATION
ALLEGHENY TECHNOLOGIES INCORPORATED
Novelis Inc.
TREDEGAR CORPORATION
MUELLER INDUSTRIES, INC.
MATTHEWS INTERNATIONAL CORPORATION
DMC Global Inc.
SILGAN HOLDINGS INC.
CROWN HOLDINGS, INC.
GREIF, INC.
THE L.S. STARRETT COMPANY
THE EASTERN COMPANY
Simpson Manufacturing Co., Inc.
STANLEY BLACK & DECKER, INC.
SNAP-ON INCORPORATED
Valmont Industries, Inc.
PGT Innovations, Inc.
Shiloh Industries, Inc.
TRIMAS CORPORATION
PARKER-HANNIFIN CORPORATION
BARNES GROUP INC.
CRANE CO.
WATTS WATER TECHNOLOGIES, INC.

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